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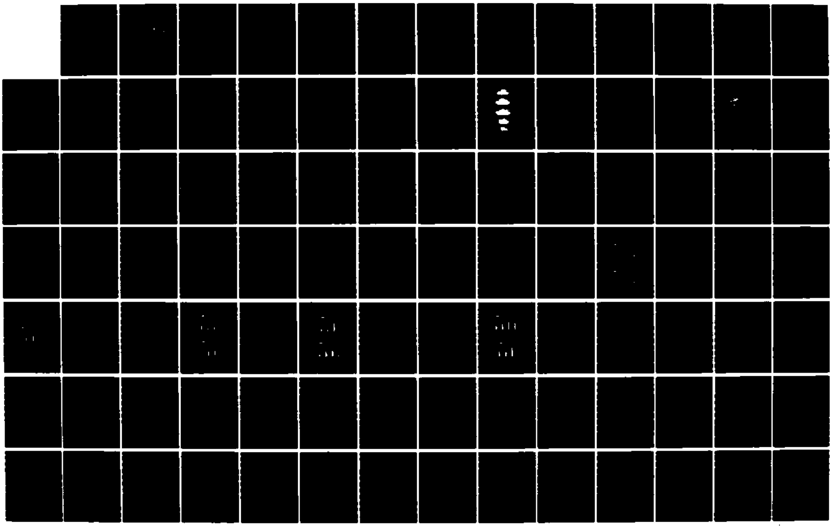

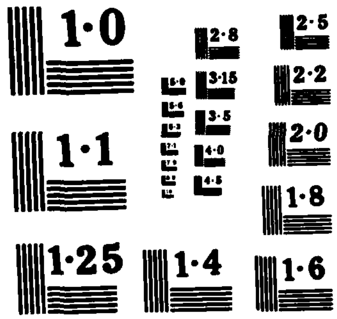

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GROUND VEHICLE CLASSIFICATION USING MULTIFREQUENCY MULTIPOLARIZATION RESONANCE RADAR

Neil Chamberlain

The Ohio State University

ElectroScience Laboratory

Department of Electrical Engineering
Columbus, Ohio 43212

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16. Abstract (Limit: 200 words)

Experiments investigating the classification of ground vehicles using processed radar returns are described. The calibrated and scaled backscatter measurements of scale-model vehicles at several azimuth angles are used to establish a catalog representing the VHF resonance region radar returns of actual vehicle targets. The performance of both the nearest neighbor algorithm, (using frequency domain data), and a correlation algorithm (using time domain data), is investigated. The effects of wave polarization, azimuth angle, and other key parameters are examined. The consequences of introducing forced errors into the estimates of aspect angle are studied. A novel feature set employing the ratio of vertically and horizontally polarized radar returns is described, and its classification performance is examined.

In general, classification is found to be very much dependent on the particular algorithm, azimuth angle and polarization of interest. The Nearest Neighbor alborithm, using Radar Cross Section Amplitudes as features, was found to perform quite well, yielding classification rates of about 90%, depending on target azimuthal angle and wave polarization. Increasing the number of classification frequncies improves performance, but only to a limit. Errors in aspect angle are found to significantly degrade classification performance.

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CHAPTER I

INTRODUCTION

The conventional radar problem has been one of finding the spatial location, or velocity or both of some target. This information can be extended to include a knowledge of the target's identity, if the operating frequencies and wave polarizations are properly chosen. More specifically, if the wavelength of the radar energy is comparable to the maximum dimension of the target (i.e., in the resonance region), then certain information, relating to the target's dimensions and shape, will be imbedded in the radar return [3].

Radars operating in the VHF band (30 to 300 MHz) have wavelengths ranging from 1 to 100 m; hence tarks, trucks, jeeps, etc., are potential candidates for resonance region target identification. Figure 1.1 shows a diagram of a VHF radar system for target classification. Typically, the radar platform might be airborne, with the radar operating in the line-of-sight mode.

The problem addressed here is one of studying the classifiability of ground vehicles using VHF radar in a representatively error prone (noisy) environment, using simulated multiple-frequency, multiple-polarization resonance radar returns. The work presented here is closely related to that of Technical Report 714190-9, "Surface ship Classification Using Multipolarization, Multifrequency Sky-Wave Resonance Radar", and consequently, that report will be referenced frequently.

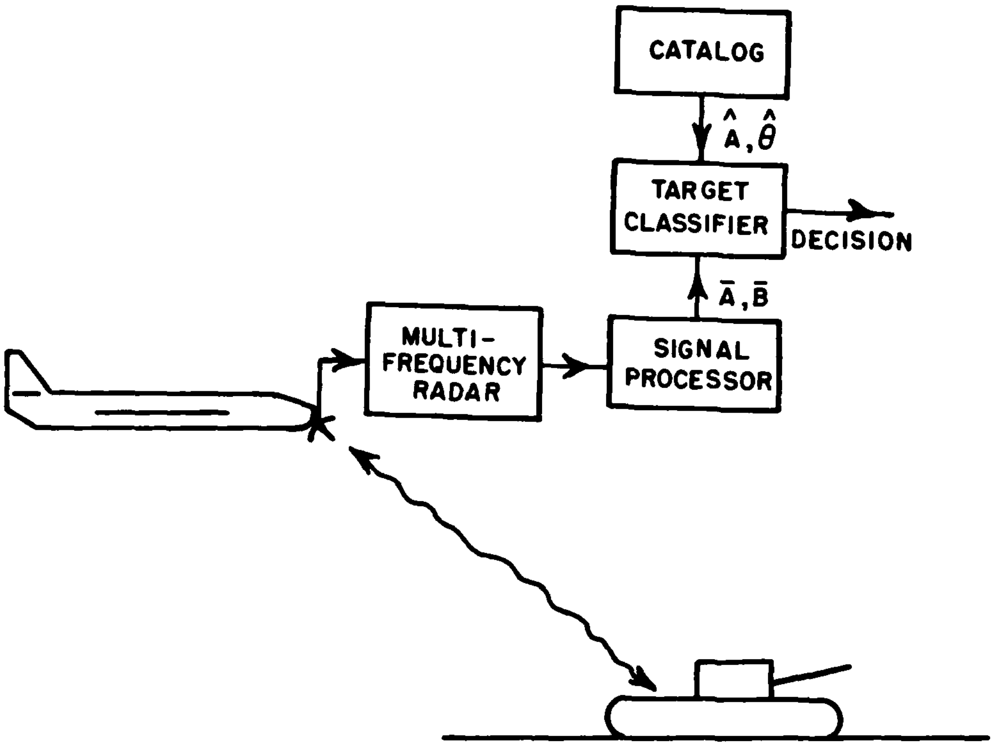

Figure 1.1 Block diagram of target classification system. The catalog contains returns of some preselected targets $(\hat{A},\hat{\theta})$. The output of the signal processor is a set of amplitude and phase returns of the unknown target.

Later in this Chapter, the general nature of the VHF radar system will be briefly discussed, along with the measurement of amplitude and phase returns. Chapter II summarizes the key points in generating a database, and outlines the classification algorithms used in the experiments. Experimental procedure and other considerations are discussed in Chapter III, along with a presentation of experimental results. Chapter IV presents a summary of the work, emphasizing the more important findings of Chapter III.

A. VHF RADAR

The purpose of the VHF Radar System is to make a set of measurements pertaining to the radar cross section of a target, which can then be processed in order to classify the target.

Typically the radar energy will be pulsed to allow estimation of range and to reduce clutter levels by range gating. If the targets are moving, doppler filtering may be used to further reduce clutter levels.

The amplitudes of the radar cross sections, A, are key target features. They can be calculated directly from Equation (1.2).

$$\sigma = \frac{\text{Scattered Power}}{\text{Incident Power Density at the Target}} \tag{1.1}$$

$$A \equiv \sqrt{\sigma} = \sqrt{\frac{P^r \, (4\pi)^3 R^4 \, L_p^{\,2} \, L_s}{P_T \, G_T \, G_R \, \lambda^2 \, G_A}} \tag{1.2}$$

where:

P_T = Transmitter power

G_T = Transmitting antenna gain

G_R = Receiving antenna gain

λ = Wavelength of propagating energy

G_A = Receiver power gain

p^r = Power received

R = Range of target

L_p = One-way propagation loss

L_s = System loss

Parameters such as L_p, the one-way propagation loss, can be estimated with a useful degree of accuracy. Generally speaking, the atmosphere, as far as direct line-of-sight propagation in the VHF band is concerned, is a non-dispersive and homogeneous medium. (An exception to this is the Troposphere, which can cause scattering of electromagnetic energy). Consequently, the range delay and hence the range of a target can be estimated quite accurately, with respect to the measurement of amplitudes.

Unfortunately, the intrinsic phase of a target's radar cross-section cannot be estimated as accurately as the amplitude. Skolnik [4] gives the R.M.S. error in range delay, δT_R, for a simple leading and trailing edge pulse detector as

$$\delta T_R \cong \sqrt{\frac{\tau}{4BE/No.}} \tag{1.3}$$

τ = Pulse width of Radar Energy (seconds)

E = Energy in a single pulse (Joules)

No = Noise power per unit bandwidth (Watts/Hz)

B = Bandwidth of IF amplifier (Hz)

If it is assumed that the bandwidth of the IF amplifier and filters is roughly equal to the bandwidth of a pulse, and that the pulse is roughly rectangular, then $B \approx 1/\tau$.

The R.M.S. range error δR is calculated as

$$\delta R = \frac{c.\ \delta T_R}{2} \quad . \tag{1.4}$$

$$\delta R = \frac{\tau c}{4} \sqrt{\frac{N}{S}} \qquad \text{(meters)} \tag{1.5}$$

where

$$N = N_o\, B \qquad \text{(Watts)} \tag{1.6}$$

$$S = E\ \tau. \qquad \text{(Watts)} \tag{1.7}$$

The term τc is the actual length of the pulse, in meters. Assuming that the pulse width is at least 20 wavelengths long, δR is given as

$$\delta R = 5\lambda \sqrt{\frac{N}{S}} \tag{1.8}$$

Such an error might be quite admissible in the estimation of amplitudes, however, its effect on phase is more serious. The error in phase resulting from this inaccuracy is given by

$$\theta_e = \frac{4\pi\delta R}{\lambda} \tag{1.9}$$

Substituting Equation (1.8) into Equation (1.9) yields

$$\theta e \approx 20\pi\sqrt{\frac{N}{S}} \quad . \tag{1.10}$$

A typical signal-to-noise ratio (S/N) might be on the order of 10 dB, resulting in an R.M.S. error, θ_e, of about 6π radians. In view of the fact that intrinsic phase values will be distributed between 0 and 2π radians, this error precludes any meaningful measurement of intrinsic phase.

One method of utilizing phase information which obviates the problems incurred by range errors is to use the parameter W [1], defined as $W_i = \theta_i \lambda_i - \theta_{i+1}\lambda_{i+1}$, where

$$W_i = 4\pi(R_i - R_{i+1}) + (\phi_i \lambda_i - \phi_{i+1}\lambda_{i+1}) \tag{1.11}$$

and

R_i = range to target at wavelength λ_i

R_{i+1} = range to target at wavelength λ_{i+1}

ϕ_i = intrinsic phase of target at wavelength λ_i

ϕ_{i+1} = intrinsic phase of target at wavelength λ_{i+1}

θ_i = measured phase of target at wavelength λ_i

θ_{i+1} = measured phase of target at wavelength λ_{i+1}.

Since the propagating medium is non-dispersive, $R_i \approx R_{i+1}$ over a wide range of frequencies (several MHz), and consequently, (1.11) reduces to

$$W_i = \phi_i \lambda_i - \phi_{i+1}\lambda_{i+1}. \tag{1.12}$$

This parameter, or more properly, feature, is used in subsequent classification algorithms.

CHAPTER II

DATABASE AND CLASSIFICATION ALGORITHMS

A. INTRODUCTION

In order to build a catalog of reference vehicle responses, a large amount of experimental data collection and processing using scaled model ships is necessary.

Firstly, the phase and amplitude returns of each model vehicle are measured at a set of frequencies, polarizations, aspect angles and elevation angles of interest. The raw data are calibrated to remove unwanted background and system response effects, and are converted into absolute radar cross section magnitude and phase. The calibrated data are then scaled in magnitude and frequency so that the responses are representative of real vehicle returns measured in the VHF band. A more comprehensive discussion of these procedures is given in [1], the main points of which are summarized below.

Measurement of Data

The measurement techniques employed in this study are virtually the same as those used for ship targets, as described in Technical Report 714190-9 [1]. However, for ground vehicles, polarization was restricted to vertical and horizontal, measurements were made using an elevation angle of 27°, and aspect angles of 0° through 90° in 10° increments (including 15° and 45°). A large flat circular groundplane was used to simulate the surface of the Earth.

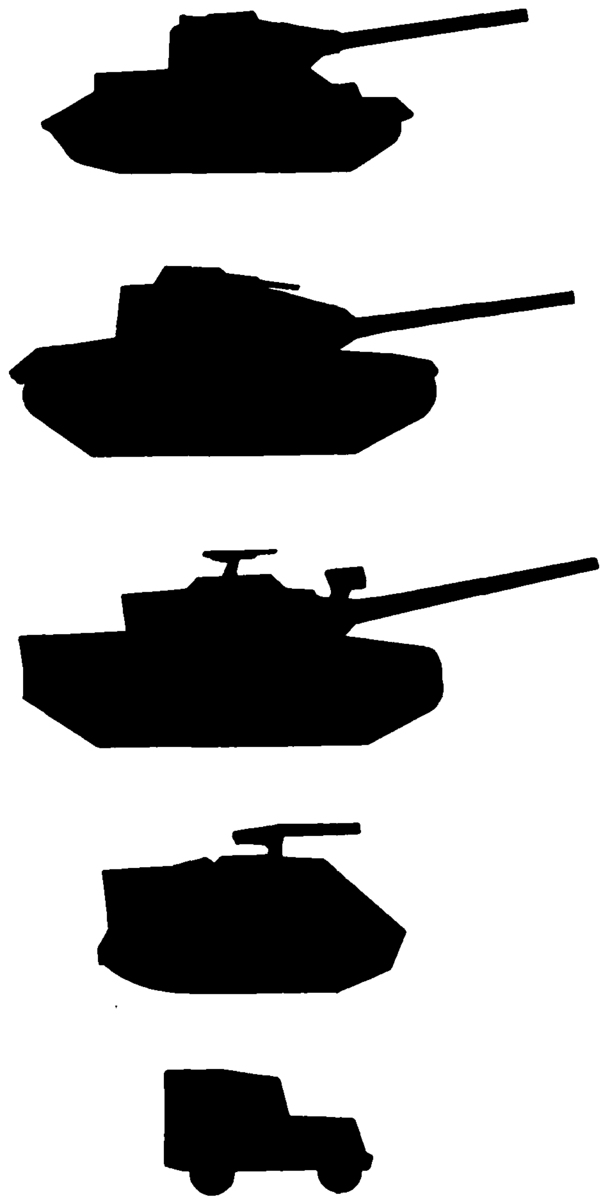

Figure 2.1 Silhouettes of the 5 ground vehicles used in classification studies.

B. CALIBRATING THE DATA

The purpose of calibrating frequency data is to remove the imbedded system characteristic. Calibration techniques are discussed by Kimball [7], and (with particular respect to targets on a ground plane) in 714190-9 [1]. In summary, the calibration procedure is as follows.

1. Remove the range delay from the measured data.
2. Subtract backgrounds from target and calibration target.
3. Remove invalid points from resulting subtractions.
4. Filter (in range) the subtracted files to further reduce background terms.
5. Calibrate the target of interest according to Equation (2.1).
6. Filter (in range) the calibrated data again if necessary.

The calibration equation is given by

$$\tilde{T}_C = \frac{\tilde{E}\,(\tilde{T} - \tilde{B}_T)}{(\tilde{S} - \tilde{B}_S)} \tag{2.1}$$

where $\tilde{T}_C$, $\tilde{E}$, $\tilde{T}$, $\tilde{B}_T$, $\tilde{S}$, and $\tilde{B}_S$ are complex phasors for each frequency defined as:

$\tilde{T}_C$, the calculated radar cross section (RCS) of the calibrated target

$\tilde{E}$, the computed (exact) RCS σ: in units of meters and absolute phase (deg.), from the calibration target.

$\tilde{T}$, the signal voltage measured with the target installed.

$\tilde{B}_T$, the signal voltage measured for the background (no target installed) associated with the target.

$\tilde{S}$, the signal voltage measured with the calibration target installed.

$\tilde{B}_S$, the signal voltage measured for the background (no target installed) associated with the calibration target.

The term $\tilde{T}$ in Equation (2.1) is a combination of backscatter from the vehicle and groundplane, and the term $\tilde{B}_T$ is the backscatter from the groundplane alone. Hence, a background (groundplane) subtraction should yield the vehicle backscatter. Unfortunately, owing to target-groundplane edge interactions and the unavoidable positional disturbance of the groundplane when the targets were installed or moved, some residual response remains at the location of the groundplane edges after the subtraction and calibration.

Post-calibration time domain windowing was used to remove these residuals as they represent a distortion of the desired vehicle data, and would be particularly disruptive in the correlation algorithm discussed later.

C. CHECKING CALIBRATED RESPONSES

Once a particular vehicle had been calibrated, its frequency response and impulse response were then generated as plots. The frequency responses were examined for 'glitches', i.e., large spikes of

about 10-100 MHz bandwidth and 10 to 30 dB in extent, caused by receiver hardware problems. Generally a glitch is hard to deal with because the phase and amplitude responses affect up to 10 points. If the glitch exists in a background or calibration target file then an alternative data file might be used. A bad glitch in a ground vehicle data file might require a new set of measurements. Small glitches, both in amplitude and bandwidth, at frequencies lower than 4 GHz can be tolerated.

The time response was the main tool for checking the validity of calibrations because the transient response gives an intuitive geometric guide to the mechanisms which cause scattering. Figure 2.2 shows a typical response, scaled 1 to 1 with the vehicle overlaid. Using templates in this way shows whether the main response confines itself to the length of the vehicle and if structures likely to cause large amounts of scattering are indeed doing so. The bandwidth of the responses is sufficiently large to provide the necessary resolution to make these judgements. Resolution in time is given by

$$\tau \simeq 1/B \tag{2.2}$$

For B = 16 GHz, then τ = 62.5 p seconds, which at the speed of light corresponds to 1.875 cm. The average length of vehicles used in experiments was about 7 cm (including gun barrels of tanks) and the average width was 2.5 cm.

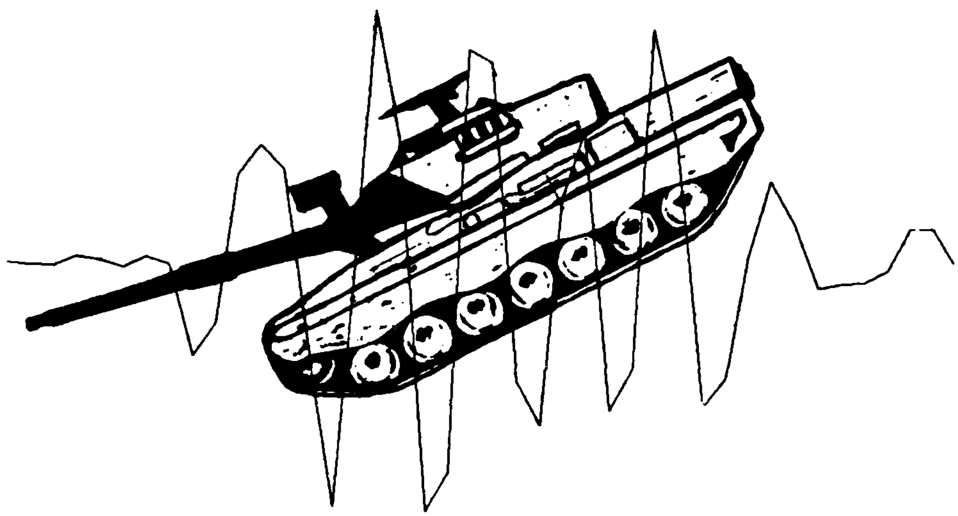

Figure 2.2 A tank scaled 1:1 with its impulse response in order to check a calibration.

D. DATA SCALING

Data collected and calibrated in the microwave region on scale models must be scaled before being used in classification algorithms. A data point is scaled in 2 ways. First, its amplitude, $\sqrt{\sigma}$, is multiplied by a scale factor, and secondly, the frequency it represents is divided by the same scale factor. Data measured in the 2 to 18 GHz microwave band was collected for models having a scale factor of 1:87. The resulting VHF band extends from 23 to 206 MHz.

Since processing frequencies may have been selected which were not actually represented by data points, it was necessary to interpolate between data points by means of a Hamming window.

A frequency increment of 0.5 MHz was selected for the 23 to 206 MHz band, with a Hamming Window width of 5 MHz. Representative scaled frequency and phase returns are shown in Appendix B. Since the validity of data near the band edges is uncertain, these frequencies are avoided in subsequent classification experiments, resulting in a net useable frequency range of 25 to 200 MHz.

A SUMMARY OF SCALED DATA GENERATION

1.	<u>Measured Data</u>	
	Amplitudes	$A_m = \sqrt{RCS} = \sqrt{\lvert\tilde{\tau}_c\rvert}$
	Phases	θ_m
	(at) frequencies	f_m : 2-18 GHz, 10 MHz steps ≡ 1601 data points
2.	<u>Calibrated Data</u>	A_c θ_c f_c : 2-18 GHz, 10 MHz steps
	Smoothing	± 3 ns (first nulls) Hanning Window equivelent to 65 point smoothing, gives a 1:25 window to bandwidth ratio.
3.	<u>Scaled Data</u>	$A_s = A_c$ SF $\theta_s = \theta_c$ (SF = Scale Factor) $f_s = f_s/SF$
		SF = 1:87 23-206 MHz, 1/2 MHz steps 366 data points Interpolation using 5 MHz Hamming Window Net frequency range: 25-200 MHz

E. TARGET CLASSIFICATION

The basic process of target classification is illustrated in Figure 2.3. The measurement system in this case is a compact radar range. It produces a measurement vector m, which is a set of calibrated RCS amplitudes and phases at a number of frequencies, aspect angles and polarizations [1]. Each measurement vector is a point in M-dimensional space (also called the observation space). The feature extractor reduces the dimensionality of the measurement vector to produce a feature vector n, which is a point in N-dimensional space (M > N). For example, if the amplitudes and phase of the RCS of a vehicle were measured at 2 polarizations, 3 aspect angles and 4 frequencies, and it is assumed polarization and elevation are known, aspect angle is unknown and only amplitudes are used to classify the target, then the feature extractor reduces a 48-dimensional space to 12-dimensional space (4 frequencies x 3 aspect angles). Essentially, the feature extractor is

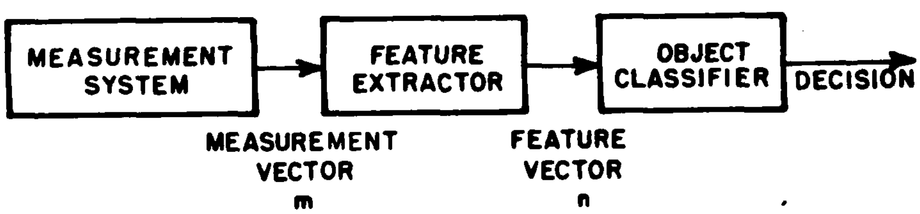

Figure 2.3 Basic process of a pattern classification system.

the mechanism by which a particular data file is addressed, since a measurement vector is usually dispersed amongst several data files. The feature vector is then passed to the object classifier which uses a particular algorithm to make a decision as to the identity of an unknown target (in our experiments, unknown targets are simulated by adding errors to known target RCS amplitudes).

The ultimate goal of a classification system is to identify targets with a minimum probability of error. Since the errors in these tests were simulated, the classification could have been a parametric procedure. However, in practice, the exact probability distributions of features in the feature space are not known, thus we must resort to non-parametric methods of classification. Two such methods which do not require knowledge of probabilistic information are the nearest neighbor algorithm [2] and the correlation algorithm [2], and are discussed below.

F. NEAREST NEIGHBOR CLASSIFICATION

The nearest neighbor (NN) algorithm uses amplitude and/or phase returns measured at a series of frequencies $f = f_1, f_2, \ldots, f_N$. (Note that, in general, the NN algorithm is applicable to both the frequency and the time domain). The amplitude is defined as the square root of the measured target cross section.

As mentioned earlier, the accurate measurement of intrinsic phase (i.e., phase attributed to the target) is precluded by errors in the measurement of target range. To circumvent this difficulty, the

differential quantity W is used and is defined as:

$$W_i = \theta_i \lambda_i - \theta_{i+1}\lambda_{i+1}$$

where

θ_i is the measured phase at $\lambda = \lambda_i$, and

$i = 1, \ldots N - 1$ (where N = Number of frequencies).

The reliability of amplitude information, A, and phase information, W, is related by a variance weighting factor β, in the NN algorithm. Strictly speaking, β is an arbitrary choice of the experimenter, but in the absence of any a priori knowledge as to the reliability of the A and W features (as was the case here) β is set to 1.

Let A_t (f_i), θ_t (f_i) be the measured target amplitude (|RCS|) and phase where i = 1, 2, ...N. Let A_j (f_i), θ_j (f_i) be the catalog of amplitude and phase values, where j is the target index, j = 1, 2, ...M. The NN algorithm is as follows:

1. Compute the differential phases

$$W_i{}^t = \lambda_i \ \theta_t \ (f_i) - \lambda_{i+1} \ \theta_t \ (f_{i+1})$$

$$W_i{}^j = \lambda_i \ \theta_j \ )f_i) - \lambda_{i+1} \ \theta_j \ (f_{i+1})$$

$$i = 1, 2, \ldots N-1$$

$$j = 1, 2, \ldots M$$

2. Calculate the sample averages of A and W in the database.

$$\mathrm{Avg}(A) = \frac{1}{MN} \sum_{j=1}^{M} \sum_{i=1}^{N} A_j(f_i) = \bar{A}$$

$$\mathrm{Avg}(W) = \frac{1}{M(N-1)} \sum_{j=1}^{M} \sum_{i=1}^{N-1} W_i^{\,j} = \bar{W}$$

3. Calculate the sample variances of A and W in the database.

$$\mathrm{Var}\ (A) = \frac{1}{MN} \sum_{j=1}^{M} \sum_{i=1}^{N} (A_j(f_i) - \bar{A})^2$$

$$\mathrm{Var}\ (W) = \frac{1}{M(N-1)} \sum_{j=1}^{M} \sum_{i=1}^{N-1} (W_i^{\,j} - \bar{W}\ )^2$$

4. Select β the variance weighting factor, and calculate K,

$$K = \sqrt{\frac{\mathrm{VAR}(A)}{\beta\ \mathrm{VAR}(W)}}$$

5. Compute the distance between the estimated target feature vector and the catalogued feature vector for each class in the database.

$$d_{t,j} = \sqrt{\sum_{i=1}^{N} (A_t\ (f_i) - A_j\ (f_i))^2 + \sum_{i=1}^{N-1} (KW_i^{\,t} - KW_i^{\,j})^2}\ .$$

$j = 1, 2, \ldots, M.$

6. Apply the nearest neighbor rule:

Choose smallest $d_{t,j}$ $\quad j = 1, 2, \ldots M.$

If $d_{t,m} = \min\ (d_{t,j})$ classify the target (t) as m.

7. Repeat experiment several times for each level of noise power. Compile statistics as a function of noise power.

G. CORRELATION CLASSIFICATION

In the NN algorithm, phase ambiguities can be reduced by employing the differential quantity W. These phase ambiguities manifest themselves as time shifts in the canonical time domain, and are reducible by means of a correlation process. The correlation algorithm [2] may, in fact, be implemented in either the frequency or time domain. (Below, the latter is used.)

1. Compute the correlation function.

$$\rho_{t,r}(k) = \frac{\mathrm{DIFT}\,[X(m)\;Y^*(m)]}{2\sqrt{\sum_{m=1}^{M} |X(m)|^2}\sqrt{\sum_{m=1}^{M} |Y(m)|^2}}$$

where

$X(m) = A_t(f_k)\exp((j\theta_t(f_k))$ t = target index

$Y(m) = A_r(f_k)\exp(j\theta_r(f_k))$ r = catalog index

$k = 1, 2, \ldots, M$

N = Number of frequencies

$m = f_1/\Delta f,\ f_2/\Delta f,\ \ldots,\ f_M/\Delta f$

$\Delta f = f_i - f_{i-1}$ $i = 1, 2, \ldots, M$

and DIFT is the Discrete Inverse Fourier Transform of the frequency domain data $(X(m)\ Y^*(m))$. Y^* is the complex conjugate of Y.

2. Choose the time shift constant k such that $\rho(k)$ is maximized. For a particular set of two targets this yields $\rho_{t,r}^{max}$, r = 1, ..., M, where M = number of catalog members.

3. Choose the largest $\rho_{t,r}^{max}$. If $\rho_{t,q}^{max} = \text{Max}\ (\rho_{t,r}^{max})$, classify the target (t) as q.

4. Repeat experiment several times for each level of noise power. Compile statistics as a function of noise power.

CHAPTER III

EXPERIMENTAL CONSIDERATIONS

A. INTRODUCTION

Figure 3.1 summarizes the experimental classification procedure in the form of a flow chart. Data for M vehicles at a total of N frequencies are contained in the database. The database is a directory of scaled data files, each corresponding to a vehicle at a particular aspect angle, elevation angle and polarization. Amplitudes and phases at the desired frequencies, aspect and polarizations are selected for each vehicle in the database to form a catelog (this is equivalent to feature extraction, see Chapter 2, Section E). This selection, in a practical situation, would be based on all of the a priori information pertaining to the unknown target. Zero mean Gaussian errors are then added to the entire catalog to produce a set of test targets. Classification proceeds for each noisy test target and decision statistics are compiled. It is worth emphasizing that in the following experiments, the whole catalog of vehicle amplitude and phase returns is corrupted by zero mean Gaussian errors and classification proceeds for each target in that "noisy catalog". At this point there are two catalogs; one an error-contaminated version of the other. The error-corrupted RCS values of the first vehicle are compared (by the various algorithms) with those of the M noise-free vehicles and a decision is

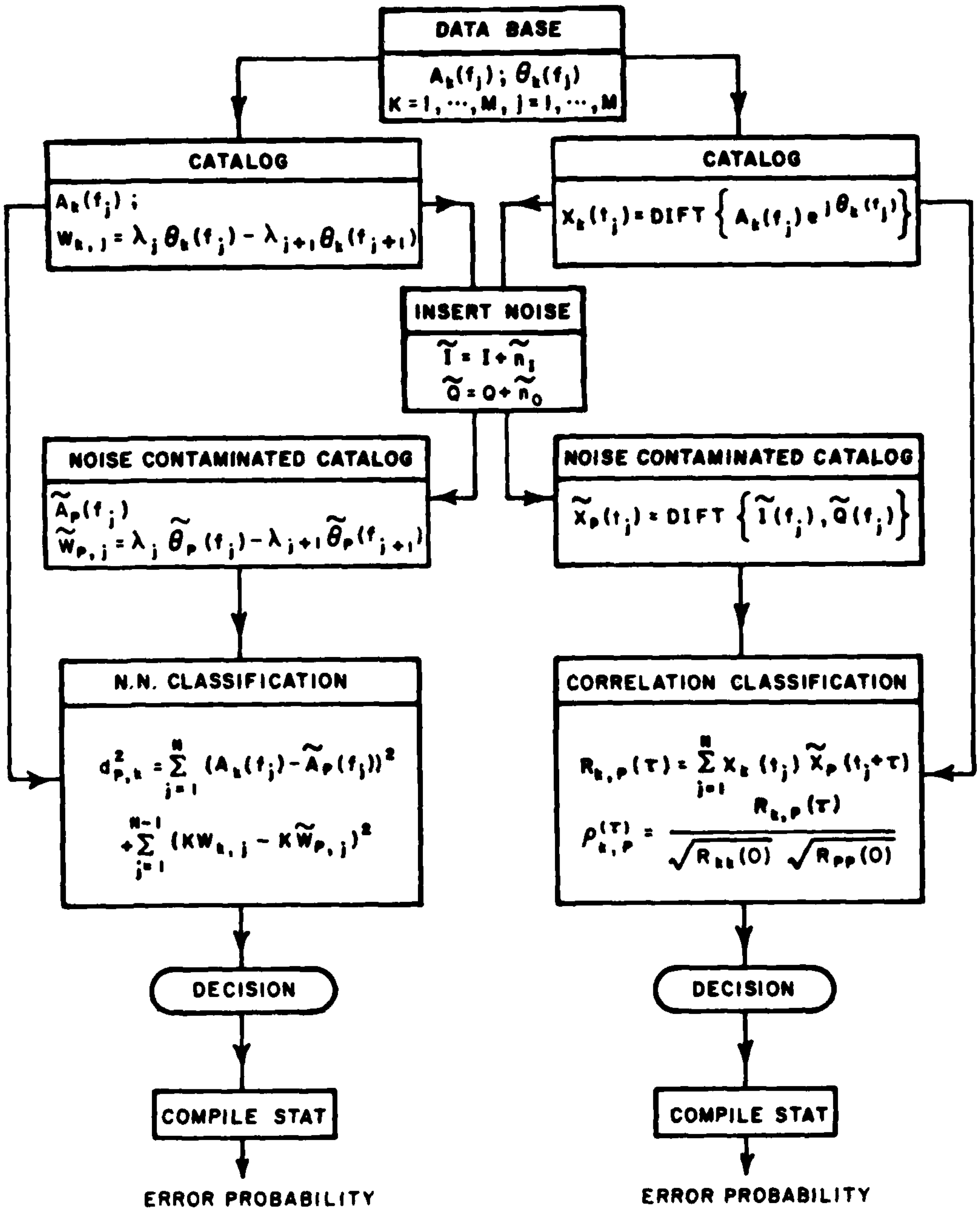

Figure 3.1 A flow chart of the experimental process of classification.

made as to the identity of the test target. Since we added the noise to the test target, we know its identity beforehand, and can therefore determine if the classification was either correct or incorrect. We say a target has been identified correctly if we choose the right vehicle at the right aspect and elevation angle. A target is misclassified if we choose either the wrong vehicle, or the right vehicle at the wrong elevation or aspect angle. This decision process is justified on the basis that we are investigating the classification properties of parameters, such as aspect angle, polarization etc., rather than the classification properties of individual vehicles.

The process is then repreated for subsequent members of the noisy catalog until all M error-contaminated test targets have been classified. The number of misclassifications is recorded for the particular level of injected noise power. Hence the statistics of the experiments apply to the collection of vehicles as a whole and classification properties between individual vehicles, although of interest, are not investigated here.

The experiment is repeated a number of times in order to compile meaningful statistics, i.e. representative curves (see below). The entire process is then repeated for a different injected noise power so that curves of misclassification percentage versus post-processing SNR can be drawn.

B. EXPERIMENTAL FREQUENCIES

The time domain impulse response has (by rule of thumb) a worst-case duration of 6 transit times across a target of length L. In order to satisfy Shannon's Sampling Theorem, we require that the frequency sampling interval should satisfy

$$\Delta f < c/6L. \tag{3.1}$$

where c is the speed of light.

The vehicle dimensions are on the order of 6 m, implying

$$\Delta f < 6 \text{ MHz}. \tag{3.2}$$

Thus, $\Delta f = 5$ MHz was selected as the frequency increment. The corresponding selection of frequencies is given in Table 3.1.

C. NOISE MODEL

Based on arguments discussed by Chen [2], and on the Central Limit Theorem, we assume a Gaussian noise model. Figure 3.2 shows a noise-free vector which is contaminated by adding in-phase and quadrature Gaussian noise components. The resultant vector has real and imaginary terms thus

$$\tilde{I} = A \cos\theta + \tilde{n}_I \tag{3.3}$$

$$\tilde{Q} = A \sin\theta + \tilde{n}_Q \tag{3.4}$$

TABLE 3.1

RANGE OF FREQUENCIES USED IN EXPERIMENTS

N = 2	25 MHz < f < 30 MHz	Varying number of frequencies
N = 4	25 MHz < f < 40 MHz	
N = 8	25 MHz < f < 60 MHz	
N = 12	25 MHz < f < 80 MHz	
Band 1	25 MHz < f < 60 MHz	Varying frequency sub-band in the available 25 - 200 MHz. (8 frequencies).
Band 2	70 MHz < f < 105 MHz	
Band 3	115 MHz < f < 150 MHz	
Band 4	160 MHz < f < 195 MHz	

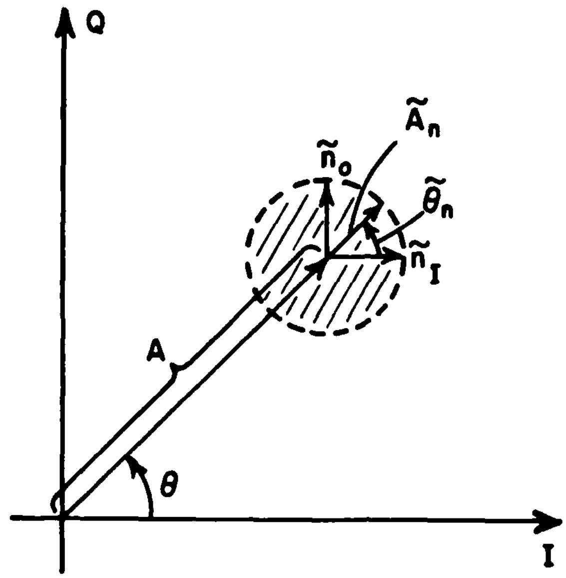

Figure 3.2 The distribution of the noise on an I-Q plane (from [2]).

where $\tilde{n}_I$ and $\tilde{n}_Q$ are independent Gaussian-distributed random variables with zero mean and variance α^2. The power in the component $\tilde{n}_I$ is equal to that of $\tilde{n}_Q$. The noise amplitude is given as

$$\tilde{A}_n = \sqrt{n_I^2 + n_Q^2} \tag{3.5}$$

and is Rayleigh distributed [5]. The noise phase is given as

$$\tilde{\theta}_n = \tan^{-1}\left[\frac{\tilde{n}_Q}{\tilde{n}_Q}\right] \tag{3.6}$$

and is uniformly distributed [5]. An expression for signal to noise

ratio is given as

$$\frac{S}{N} = \frac{I^2 + Q^2}{VAR(\tilde{n}_I) + VAR(\tilde{n}_Q)} = \frac{A^2}{\alpha^2} \tag{3.7}$$

where

α^2 is the noise power, and

A^2 is the average signal power estimated as

$$A^2 = \frac{1}{NF \cdot NS} \sum_{i=1}^{NF} \sum_{j=1}^{NS} A_{ij}^2$$

where

A_{ij} is the amplitude for the i^{th} frequency and the j^{th} vehicle

i is a frequency index, i = 1,2, ..., NF = number of frequencies.

and

j is a target index, j = 1,2, ..., NS = number of vehicles.

D. ESTIMATION OF THE PROBABILITY OF MISCLASSIFICATION

Chen [2] used the Maximum Likelihood Estimate (MLE) [6] as the estimate of probability of error for a given target;

$$PE \cong \hat{P}_E \tag{3.8}$$

where PE is the probability of error the $\hat{P}_E$ is the MLE of the probability of error. The proximity of the terms expressed in the equation above is usually stated in terms of confidence interval. For example, a 90% confidence interval at 30% error (a typical error value) for 10 targets and 50 experiments is

$$PE = \hat{P}_E \pm 3.4\% \qquad (3.9)$$

It must be emphasized that the confidence interval is not an expression of probability, i.e., the above calculation does not show that 9 times out of 10 the actual probability of error at 30% misclassification will be within ±3.4% (or 26.6% < PE < 33.4%). In regard to this, we must view confidence interval as an indication of the accuracy of a measured result, not as an absolute probability.

In classification experiments, the MLE of the probability of error is estimated by finding the percentage of misclassification to total number of experiments.

E. POST PROCESSED SIGNAL TO NOISE RATIO

We define post-processing signal-to-noise ratio (post-processing SNR) as the ratio of signal power to error variance after the received waveform has been processed to produce a final best estimate of the amplitude or phase, or both, of the target radar cross section.

In future experiments, 10 dB post-processing SNR will often be used as a reference value when comparing misclassification percentages. We do this mainly because the level of 10 dB starts to give us "useful" values of misclassification percentage, (30% and lower), and therefore represents a region of interest.

In a real situation, several measurements of a target's radar cross-section will be made, and the 10 dB figure represents an integrated SNR over the several measurements. To this extent, it is

assumed that the radar system designer can provide us with RCS measurements at a nominal 0 dB post-processed SNR and that integration of measurements will yield the "useable" 10 dB or better post-processed SNR.

CHAPTER IV

EXPERIMENTS

A. INTRODUCTION

This chapter presents most of the experimental work done in this study. The purpose of the experiments discussed here is to study classification behavior under a wide variety of the available classification parameters. These are listed below (a list of commonly used terms is given in Table 4.1).

1. Frequency Band (in the allotted 25-200 MHz)
2. Number of Frequencies and Algorithm
3. Polarization
4. Aspect Angle
5. Error in Aspect Angle

If each of these parameters were to be assessed in terms of the others, thousands of curves would be needed. Clearly this is not practical; however, an intelligent approach toward choosing the experiments allows a thorough investigation without incurring excessive data processing.

First, experimenting with a sub-band in the 25-200 MHz band indicates the best region of frequencies (if any) for a particular type

TABLE 4.1

DEFINITIONS

1. ASPECT ZONE: A small range of aspect angles centered on or adjacent to a particular aspect angle.

Aspect Zone	Name	Aspect Angles
0°	Nose-On	0°, 10°
45°	-------	40°, 45°, 50°
90°	Broadside	80°, 90°

2. KNOWN ASPECT: If vehicle data having more than one aspect angle is used in a classification, then the aspect angle is assumed known when the algorithm only allows comparisons between an 'unknown' noisy target at aspect θ_K, with 'noise-free' catalog targets at the same aspect angle θ_K. The same follows for known elevation.

3. UNKNOWN ASPECT: If vehicle having more than one aspect angle is used in a classification, then the aspect angle is assumed unknown when the algorithm only allows comparisons between an 'unknown' noisy target at aspect θ_K, with all 'noise-free' catalog targets at the same aspect angles used in the classification.

4. ALGORTHIM: One of the following:

    1. Nearest neighbor (NN), using any of the features listed in 5.

    2. Correlation Algorithm.

5. NN ALGORITHM FEATURES:

    A   Amplitude only

    W   Differential phase only

    AW   Amplitude and differential phase

    Note that, in general, the term 'feature', in the context of resonance region radar returns, applies to any property or quality associated with the returns. This includes, for example, the magnitudes of the time domain impulse response.

TABLE 4.1

(Continued)

6. PARAMETER: A variable in the measuremet or classification process such as frequency, aspect angle, elevation angle, polarization, feature or algorithm.

7. DATA BASE: A collection of data files containing a measurement vector for each vehicle.

8. CATALOG: A single 2-dimensional complex array containing the amplitudes and phases of all vehicles at the selected frequencies, and other parameters.

9. FEATURE VECTOR: A single vector for a particular target, dimensional in frequency or time, derived from the catalog by selecting a particular feature.

10. POLARIZATION: One of the following:

    1. Vertical, V (send vertical polarization, receive vertical)

    2. Horizontal, H (send horizontal polarization, receive horizontal)

    3. Vertical divided by horizontal, V/H.

    The term described in 10.3 is not really a polarization scheme, in the sense of the preceding three terms, but is called a "polarization" for convenience. Strictly speaking, the polarization of a wave describes the instantaneous orientation of the electric field vector; the terms listed above refer to a particular measurement scheme or use of radar cross section returns, with respect to polarization.

of classification. Second, an evaluation of classification performance as a function of the number of frequencies (NF) provides a comparison with work presented in [1] and also establishes the ranking of a particular number of frequencies. Hence we can choose NF=8 for subsequent experiments and refer to this section for results pertaining to other values of NF. The problem of choosing the desired classification frequencies is thus solved.

The remaining parameters are then classified using various features and algorithms, polarizations and aspect zones. It must be remembered that certain parameters, such as V/H polarization, are not really tested in these experiments since the difficulties which they were designed to overcome were not simulated. V/H polarization purportedly has the property that multiplicative errors cancel out by virtue of the division of a vertically polarized phasor by a horizontally polarized phasor. To test the validity of this assumption, the vehicle data must be contaminated with multiplicative noise before classification proceeds. This was not done, because a reliable multiplicative noise model was not available at the time of experimentation.

In the following sections, each experiment is introduced, detailing the aim of the experiments with a brief discussion of any relevent points. The results of all experiments in the form of misclassification percentage versus post-processing SNR curves, are contained in Appendix A. These results are summarized by means of histograms representing averaged misclassification percentage at 10 dB post-processing SNR, and are presented, along with typical misclassification curves.

Conclusions drawn from the histograms often compare the classification performance of one parameter with the performance of another by saying that misclassification percentage (at 10 dB post-procssing SNR) is higher or lower by x%; here x is always the difference between the misclassification percentages, not the percentage increase of one misclassification percentage compared with another.

TABLE 4.2

INTERPRETATION OF HEADERS IN CLASSIFICATION RESULTS

The data presented in subsequent sections were plotted with an automatic header system to aid the batch processing of classification experiments. The header comprises of up to 11 lines and these are described as follows:

1. LINE 1. TARGET TYPE. i.e., ships, aircraft, ground vehicles, etc.

2. LINE 2. POLARIZATION. This can be either vertical ('V'), horizontal ('H'), cross ('X') or vertical divided by horizontal ('V/H'). The polarization for each curve is printed if this varies from curve to curve.

3. LINE 3. A PRIORI KNOWLEDGE OF ELEVATION ANGLE. This can be either 'known', 'unknown' or 'known/unknown' if some of the curves use known elevation angle and others use unknown elevation angle. The system is specific about which is known and which is unknown only if 2 curves are present.

4. LINE 4. ELEVATION ANGLE(S). This is '27' for 27°.

5. LINE 5. A PRIORI KNOWLEDGE OF ASPECT ANGLE. This is compiled in the same way as LINE 3.

6. LINE 6. MINIMUM, MAXIMUM AND INCREMENT OF ASPECT. The minimum and maximum aspect angles can be any of those discussed in Chapter 2, Section A. If these parameters vary from curve to curve, they are printed out for each curve in the same way as LINE 4 (or LINE 2).

7. LINE 7. NUMBER OF FREQUENCIES. This is printed for each curve.

TABLE 4.2

(Continued)

8. LINE 8. NUMBER OF TARGETS. This is always a multiple of 5, the number of vehicles (No. of targets = 5 x No. aspect angles x No. elevation angles). This is printed for each curve.

9. LINE 9. 90% CONFIDENCE INTERVAL AT 30% MISCLASSIFICATION. This is calculated according to the discussion in Chapter 3, Section D, and is printed for each curve.

10. LINE 10. CLASSIFICATION FEATURES. These are listed as:

'A'	Amplitudes only	NN algorithm
'W'	Differential phases only	
'AW'	Amplitudes and phases	
'T'	Correlation algorithm.	

11. LINE 11. IDENTITY OF CURVES WITH ASPECT OR ELEVATION ANGLE ERRORS. This is printed only if there is an error in elevation angle or aspect angle. Note that the classification software does not allow both types of errors at once. For example, if 3 curves were plotted and the last two had aspect errors, LINE 11 would read

'ASPECT ERR IN CURVE 2 3'

Curves are identified as follows:

Curve 1
Curve 2
Curve 3
Curve 4
Curve 5
Curve 6

B. FREQUENCY BAND

1. INTRODUCTION

This set of experiments was designed to examine the effect of choosing a particular frequency band for various aspect angles and polarizations. In each experiment, the Nearest Neighbor algorithm with the 'amplitudes only' (A) feature was used.

The availalbe band of 25-200 MHz was split into 4 non-overlapping sub-bands, (see Table 3.1) each contianing 8 discrete frequencies separated by 5 MHz.

Generally, it is expected that the lower bands of frequencies will provide the best classification performance. This is because the RCS at lower frequencies tends to vary less per unit bandwidth compared with higher frequencies. Consequently, for higher frequencies, (in the upper resonance region) a small change in a parameter such as aspect angle, or the addition of noise to the RCS amplitudes results in a greater change in the selected features compared to the change at lower frequencies. In this sense, the RCS frequency response is more reliable (i.e., impervious to small changes in orientation, frequency, etc.) at lower frequencies than at higher frequencies.

2. RESULTS AND CONCLUSIONS

Figures 4.1 and 4.2 show a summary of classification results by means of average misclassification percentages at 10 dB post-processing

SNR. The curves from which these histograms are extracted are contained in Appendix A.

From Figure 4.1 it is evident that for vertical and horizontal polarizations, there is a small but distinct preference for the lower frequency band. However, V/H polarization does not follow this pattern, and favors band 4.

Figure 4.2 shows that there is no distinct nor significant preference for a particular sub-band, with respect to aspect zone. This result is similar to the finding in the classification of ship targets [1].

Averaging across all parameters, band 2 does best with 6% misclassification and band 3 does worst with 12% misclassification. In general though, the distinct preference for lower frequencies established by ship targets, is not so marked for the case of ground vehicles. Figures 4.1 and 4.2 also show that the variation of performance with different bands is not great, indicating that selection of frequencies in the classification of ground vehicles is not a critical parameter (at least with the 25-200 MHz band used in these experiments).

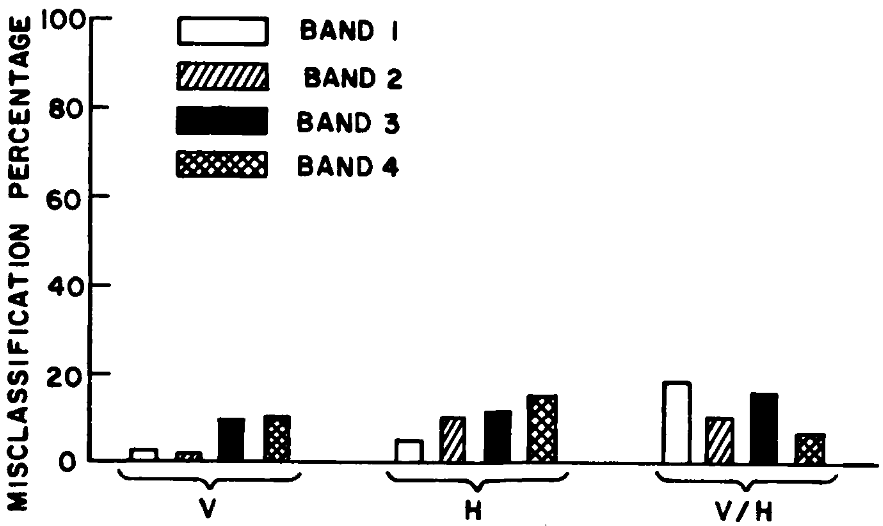

Figure 4.1. Classification performance of various sub-bands in the available 25-200 MHz band, as a function of polarization.

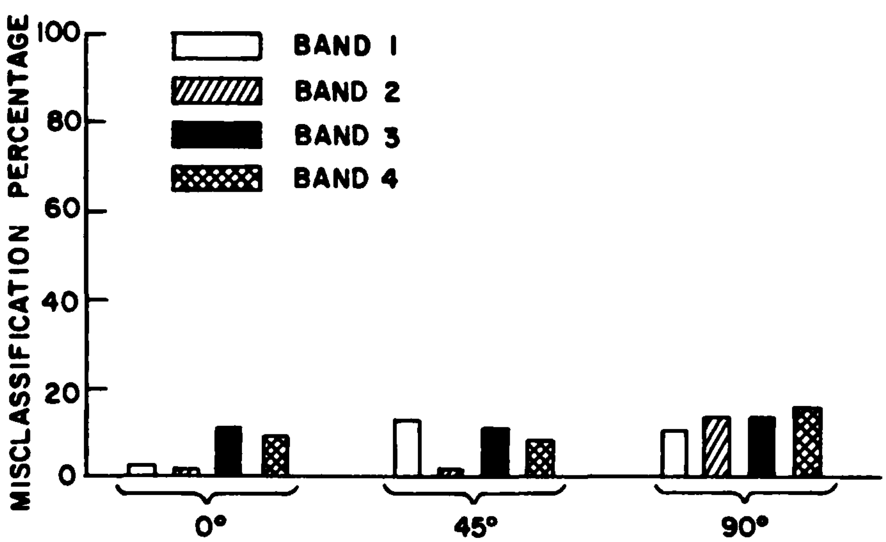

Figure 4.2. Classification performance of various sub-bands in the available 25-200 MHz band, as a function of aspect zone.

C. NUMBER OF FREQUENCIES AND ALGORITHM

1. INTRODUCTION

The purpose of this experiment was to examine how the number of classification frequencies affects other classification parameters, such as polarization, aspect angle and algorithm. In subsequent experiments, 8 frequencies are used; the classification performance for other numbers of frequencies can then be extrapolated from results obtained in this experiment. Three feature (A, AW, W) from the NN algorithm, and the correlation algorithm were evaluated at 2, 4, 6, 8 and 12 frequencies, using vertical polarization 27° elevation and aspect zones of 0°, 45° and 90° (aspect angles assumed known).

2. RESULTS AND CONCLUSIONS

Figures 4.3 through 4.5 all show that classification performance improves monotonically with the number of frequencies, with 2 frequencies yielding most misclassifications and 12 frequencies yielding the least. This result is intuitively reasonable, since a larger number of frequencies means we have more information concerning a target, and the more information we have, the more likely we are to classify it correctly.

From Figure 4.3, it is evident that vertical polarization provides best performance, followed by horizontal, then V/H polarization. Furthermore, these results apply for all numbers of frequencies. In

addition to this, if the misclassification percentage at 8 frequencies is relatively low, the reduction in misclassification percentage, when going from 8 to 12 frequencies, is relatively small. (e.g., vertical polarization: 10% misclassification at NF=8, 8.5% at NF=12). On the other hand, this reduction is relatively large when the level of misclassification at 8 frequencies is relatively high (e.g., V/H polarization: 32% at NF=8, 25% at NF=12). Hence the advantage of using a higher number of frequencies depends on the misclassification levels of a particular parameter; the higher levels (20% and above) yielding greater improvements.

Figure 4.4 shows a general preference for 0° aspect zone, which is shared somewhat by 90° aspect zone for 8 and above frequencies. As in the case of vertical polarization, 0° aspect zone shows little reduction in misclassification percentage when going from 8 to 12 frequencies.

Generally speaking, for 4 or more frequencies, the correlation algorithm provides best performance, followed by A, then AW, then W. However, for 2 frequencies, the correlation algorithm, 'T', gives almost the worst performance. If one thinks of the correlation process as a time domain operation, then it becomes clear that the resulting resolution will be poor because 2 frequencies is the absolute minimum for the Inverse Fourier Transform. Figure 4.5 also shows that a higher number of frequencies is more effective in reducing misclassifications when the algorithm is relatively favorable (e.g., 'A', 'T') compared to an algorithm which is relatively unfavorable (e.g., 'AW', 'W').

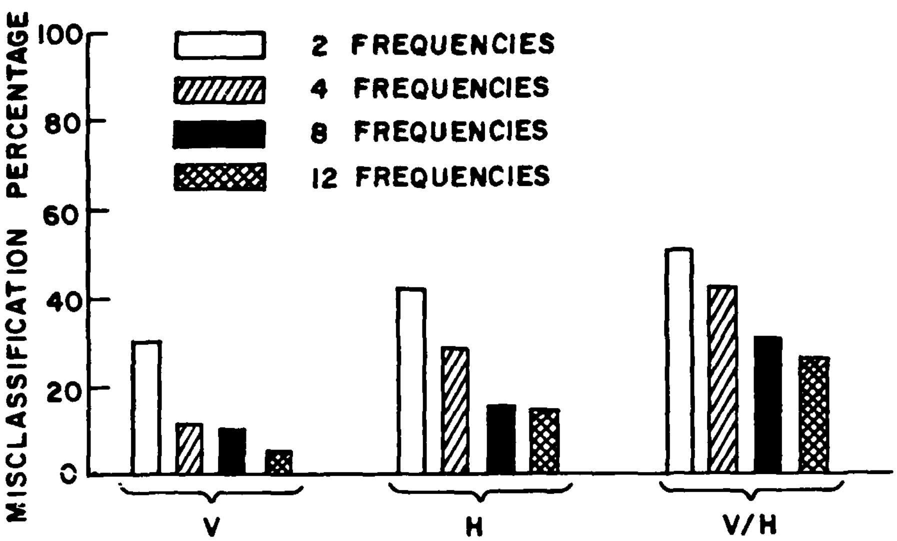

Figure 4.3. Classification performance of various numbers of frequencies as a function of polarization.

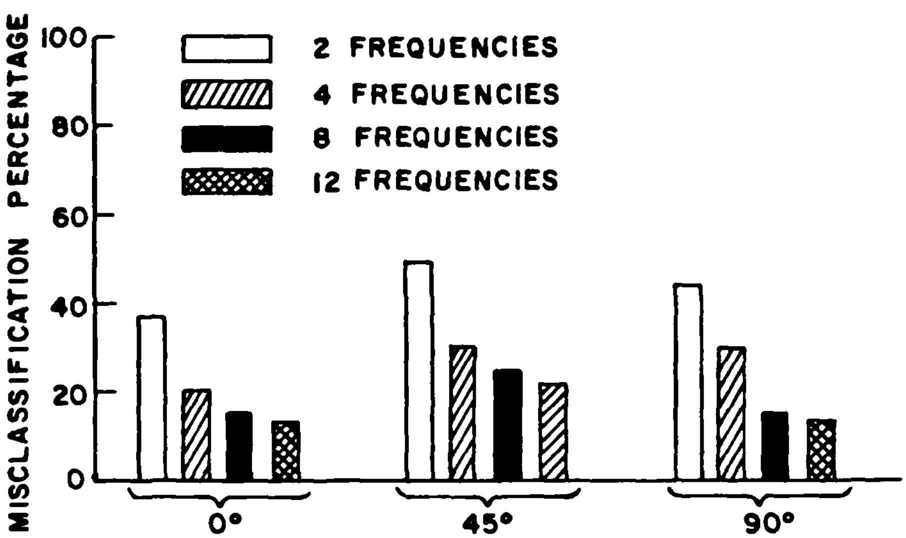

Figure 4.4. Classification performance of various numbers of frequencies as a function of aspect zone.

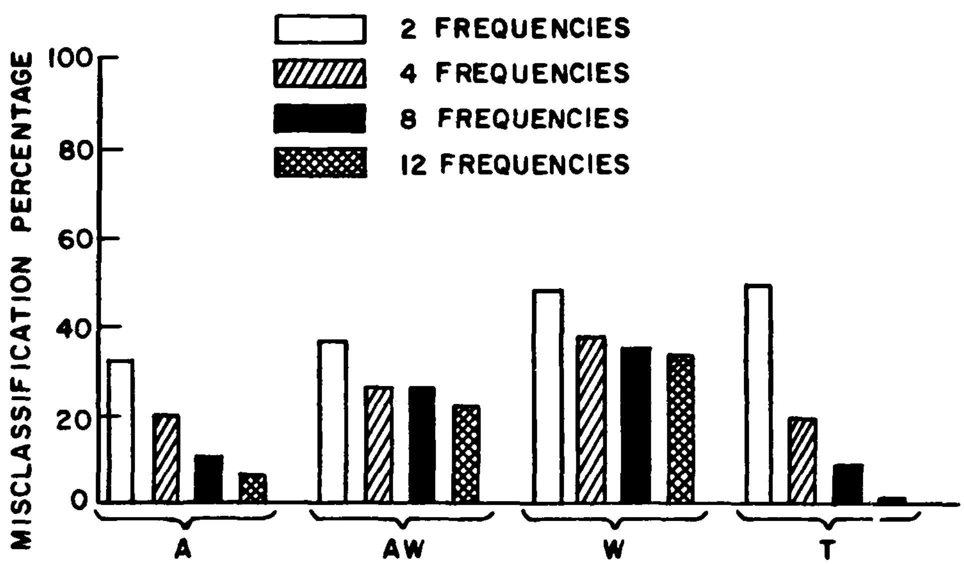

Figure 4.5. Classification performance of various numbers of frequencies as a function of algorithm.

Although it was stated that the correlation algorithm had best performance (at least for 4 and above frequencies), this performance is not substantially better than the NN algorithm using amplitudes only (1 or 2% difference). Furthermore, the correlation algorithm requires both amplitude and phase information, the latter not always being readily available. In view of these facts, and also of the correlation algorithm's poor performance with only two frequencies, 'A' must be regarded as having best all-around performance, since it provides near-best performance for the minimum of information, consistently over a range of NF.

The NN algorithm using amplitudes, 'A' and relative 'phases' W, seems to always have worse classification performance than 'A' alone. This finding runs contrary to intuition, where one would expect the addition of phase information to improve the chances of correct classification. This anomaly has been the subject of further research and as yet, has not been resolved.

D. POLARIZATION

1. INTRODUCTION

The purpose of this experiment was to determine the relative classification performance of each polarization; vertical, horizontal and vertical divided by horizontal, as a function of aspect zone and algorithm. Eight frequencies were used in this experiment.

2. RESULTS AND CONCLUSION

Figure 4.7 shows that, for each algorithm, there is a distinct preference for vertical polarization, followed by horizontal, with V/H polarization generally doing worst. At 45° aspect zone (Figure 4.6) V/H is particularly bad, with an average misclassification level of 47%.

Horizontal polarization is best at 45° and worst at 0°. For the case of ship targets [1], horizontal polarization was better at 90° than at 0° aspect zone (which is the case here). However, for vertical polarization, ground-vehicles were more readily classified at 90° aspect zone (5% misclassification on average) compared to 0° aspect zone (10% misclassification). This is opposite to the finding for ship targets, where vertical polarization favored 0° aspect zone.

For ship targets, it was fairly easy to attribute classification results to the more likely scattering mechanisms associated with a particular orientation and polarization. This was due mainly to the 'distinctness' of the ship structure; being long and thin, and usually with two or more vertical structures such as masts. Ground vehicles are more amorphous in their shape being fairly squat and featureless, bar the gun turrets of tanks. Hence, for the case of ground vehicles, it becomes more difficult to justify results in terms of possible scattering mechanisms.

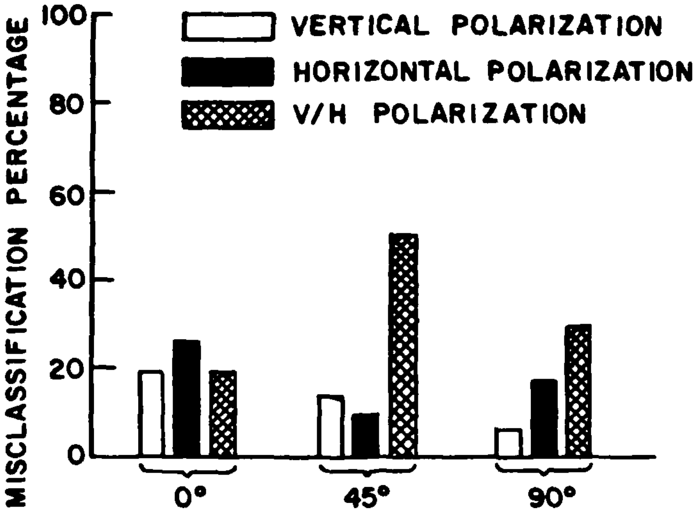

Figure 4.6. Classification performance of various polarizations as a function of aspect zone.

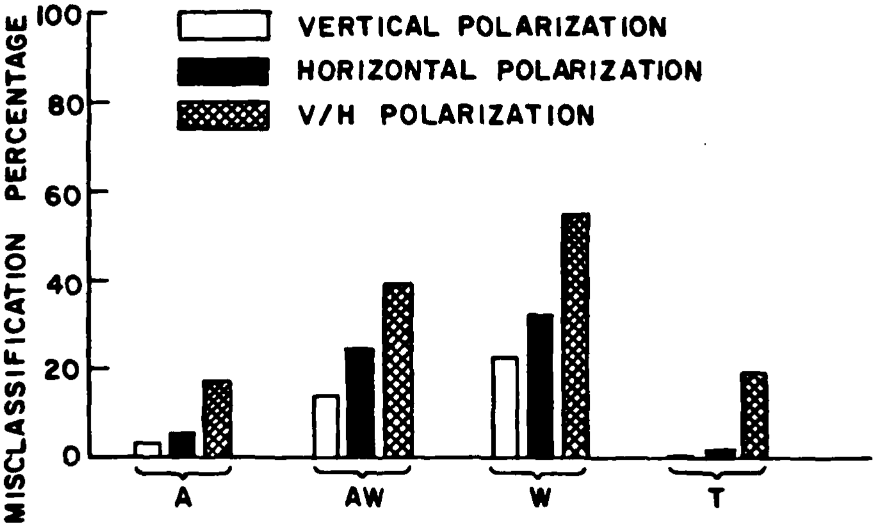

Figure 4.7. Classification performance of various polarizations as a function of algorithm.

E. ASPECT ZONE

1. INTRODUCTION

This experiment was designed to investigate how classification is affected by a particular aspect zone. From the above experiments, it is evident that classification performance is dependent on the azimuthal orientation of the ship (i.e., aspect angle) and hence, a thorough investigation of classification performance at given aspect angles is of interest.

Classification performance of three aspect zones; 0°, 45° and 90° were examined as a function of polarization (V, H, V/H) and algorithm (A, AW, W, T). Eight frequencies were used in each experiment.

2. RESULTS AND CONCLUSIONS

Figure 4.8 illustrates the classification performance at various aspect zones, for different polarizations. It is evident that the performance at any one particular aspect zone is dependent on the polarization, and that in general, no single aspect zone has a superior performance. Hence, while 90° aspect zone has best classification performance using vertical polarization, it is not so good when horizontal polarization is used (45° aspect zone being favored).

The results depicted in Figure 4.9 tend to amplify the above findings. The fact that 45° aspect zone appears to have the poorest performance for each algorithm is due to the particularly bad performance of 45° aspect zone using V/H polarization (see Figure 4.8). This tends to bias the result, somewhat, when the average values used in these histograms are derived.

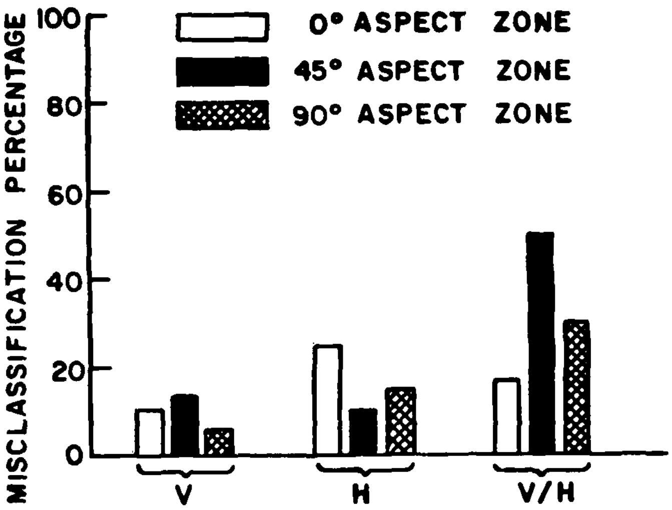

Figure 4.8. Classification performance of various aspect zones as a function of polarization.

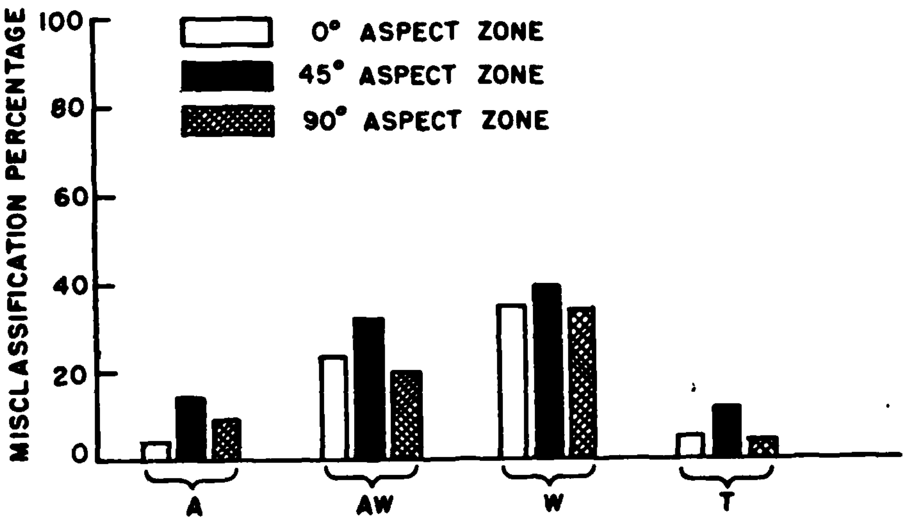

Figure 4.9. Classification performance of various aspect zones as a function of algorithm.

F. ERROR IN ASPECT ANGLE

1. INTRODUCTION

The heading of a moving vehicle, and hence its aspect can be found quite accurately by simply plotting its position at two instances of time. Knowing the time interval and range between the reference positions allows the average velocity to be calculated, and this in conjunction with the doppler shifts at the two positions allows the aspect measurement to be refined.

The aspect angle of a stationary target is more difficult to estimate, and it is possible that such an estimation might contain a large error.

The purpose of this experiment was to examine classification performance as a function of various parameters when an aspect error is introduced. For 0° aspect zone, using 0° and 10° aspects, a ± 10° error was simulated by comparing 0° error-contaminated ship returns with 10° catalog ship returns and vice versa. A 45° aspect zone, a ± 5° error was introduced using a catalog comprising vehicle returns at 40°, 45° and 50°. At 90° aspect zone a ± 10° error was used with data at 80° and 90° aspect.

2. RESULTS AND CONCLUSIONS

In general, Figures 4.10 and 4.11 reveal that an error in aspect angle results in a significant degradation in classification performance. Comparing Figures 4.10 and 4.8, an error in aspect angle

increases misclassification by between 10% and 20%. No single polarization, or aspect angle seems immune to the effects of an error in aspect angle. The correlation algorithm (T) seems to be particularly affected by the forced error, with an average increase of about 40% misclassification over the no-error case.

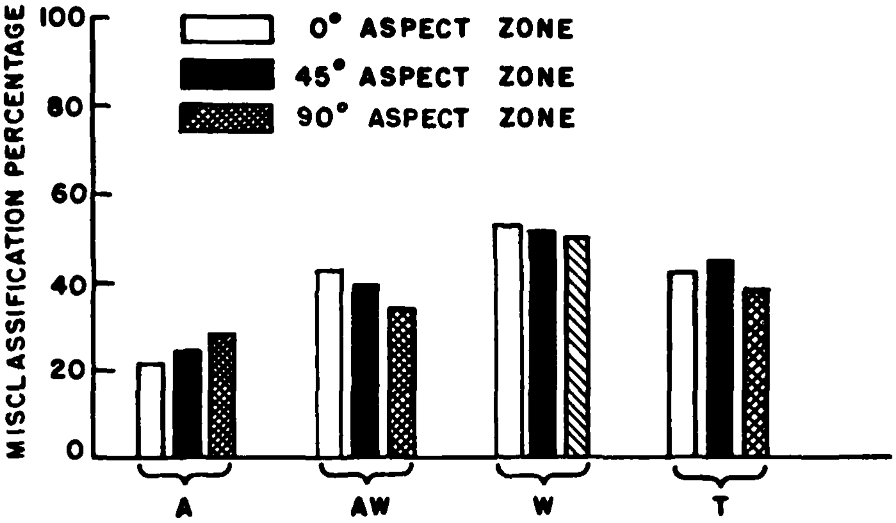

Figure 4.10. Classification performance of various aspect zones with forced errors in aspect angle, as a function of polarization.

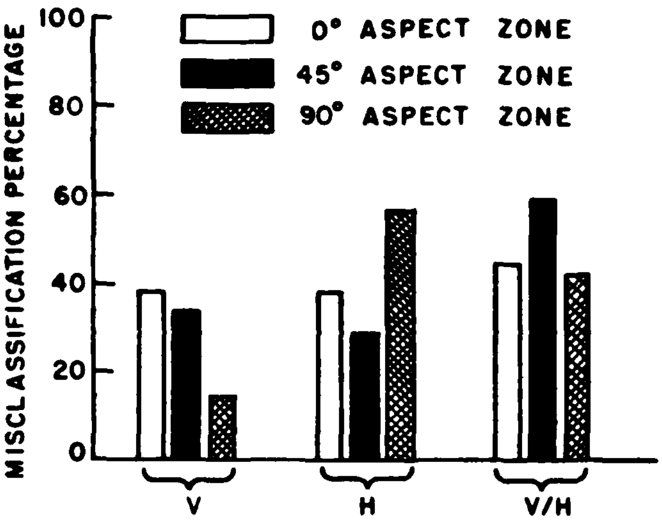

Figure 4.11. Classification performance of various aspect zones with forced errors in aspect angle, as a function of algorithm.

CHAPTER V

CONCLUSIONS

A series of experiments investigating the classification properties of a group of ground vehicles at various azimuthal (aspect) angles, using a variety of polarizations were performed. These experiments were intended, to a certain extent, to represent classification based on VHF resonance radar. A number of important findings follow from the work.

Of primary importance is the fact that it is possible to identify ground vehicle targets in a representatively error-prone environment, at "useful" classification rates. For example, at 10 dB post-processing SNR, the database of vehicles were classified at an average rate of 90%, using 4 classification frequencies and vertical polarization. Furthermore, we can discriminate effectively among tanks, APC's and jeeps, even though the general shape of the vehicles is quite similar.

It is also encouraging that the NN algorithm, incorporating the simple amplitude-only feature, performed quite well. (About 10% misclassification for 4 frequencies, and 3% for 8 frequencies, using vertical polarization). In view of the relative simplicity of acquiring the amplitude-only features (compared with the acquisition of phase data) this is a particularly useful result.

Generally speaking, the classification performance of the vehicle set was found to be dependent on both aspect zone and polarization. However, no single polarization or aspect zone proved to be substantially superior. For example, while horizontal polarization gave lowest misclassifications at the 45° aspect zone, this was not the case at the 90° aspect zone, where vertical polarization had lower misclassifications. The rate of misclassifications using vertical and horizontal polarization was found to range from 10% to 20%, depending on the azimuthal orientation of the target. This shows that, while some advantage is gained from having a dual-polarization radar system, the consequences of not having polarization agility are not drastic.

The classification performance of V/H polarization was found to be generally poorer than that of either vertical or horizontal polarization. The original impetus for the use of this V/H feature stemmed from the fact that such a division of RCS amplitudes would tend to reduce the effect of multiplicative errors. (A possible source of multiplicative noise might be foliage.) If such errors were present in the RCS data, then the V/H features might prove to classify better than either the vertical or horizontal polarization features. Hence the relatively poor performance of V/H polarization should be viewed with this potential advantage in mind.

The introduction of a small, forced error in aspect angle was found to significantly degrade classification performance, with misclassification percentages of 30% and above being typical. However, additional research in this area has revealed that the majority of

misclassification at 10 dB post-processing SNR are the right target type, but at the wrong aspect angle. For reasons stated earlier, a target classified correctly by type but incorrectly by aspect angle was considered to be a misclassification. In practice it does not matter if the aspect angle is wrong, as long as the target type (i.e., Tank 3, Jeep 1, etc.) is correct. Hence the consequences of inaccurately estimating the aspect angle of a target, ($\pm 10°$ errors in these experiments), are not as severe as first suggested by the results. A limited study showed that, if an error of $\pm 10°$ is made in the estimation of aspect angle, then the misclassification percentage at 10 dB post-processing SNR increases by only 2 or 3 percent.

Clearly, there is a substantial potential for further work using this database of 5 ground-based vehicles. New classification algorithms and techniques are currently being developed. As classification procedures gradually become more refined, we expect to see classification rates improve on the already useful values demonstrated in this study.

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APPENDIX A

CLASSIFICATION RESULTS

This appendix contains plots of misclassification percentage versus post-processing signal-to-noise-ratio for the experiments of Chapter IV. A guide to interpreting the headers of these curves is given in Table 4.2.

CLASSIFICATION OF GND VCLS
POLARIZATION V
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN
MIN,MAX,INC ASPECT 0 10 10
NO OF FREQUENCIES 8 8 8 8
NO OF TARGETS 10 10 10 10
90% CI (@30%) +/- 3.4% 3.4% 3.4% 3.4%
CLASS. FEATURES A A A A

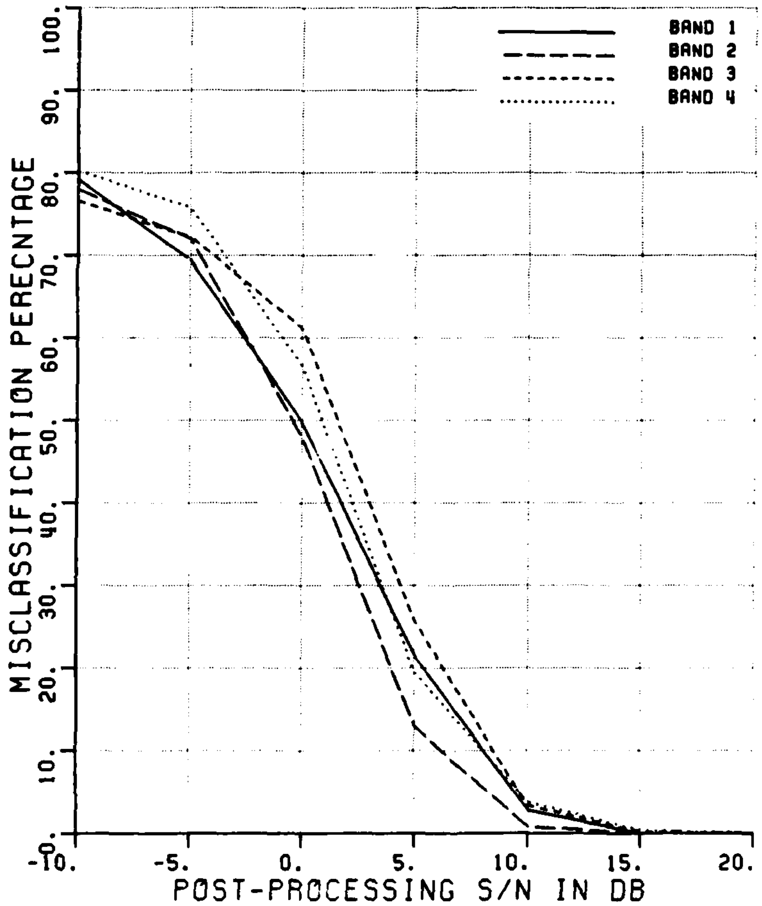

Figure A.1 Misclassification percentage versus post-processing SNR, comparing the performance of 4 sub bands in the 25-200 MHz band.

CLASSIFICATION OF GND VCLS
POLARIZATION H
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN
MIN,MAX,INC ASPECT 0 10 10
NO OF FREQUENCIES 8 8 8 8
NO OF TARGETS 10 10 10 10
90% CI (@30%) +/- 3.4% 3.4% 3.4% 3.4%
CLASS. FEATURES A A A A

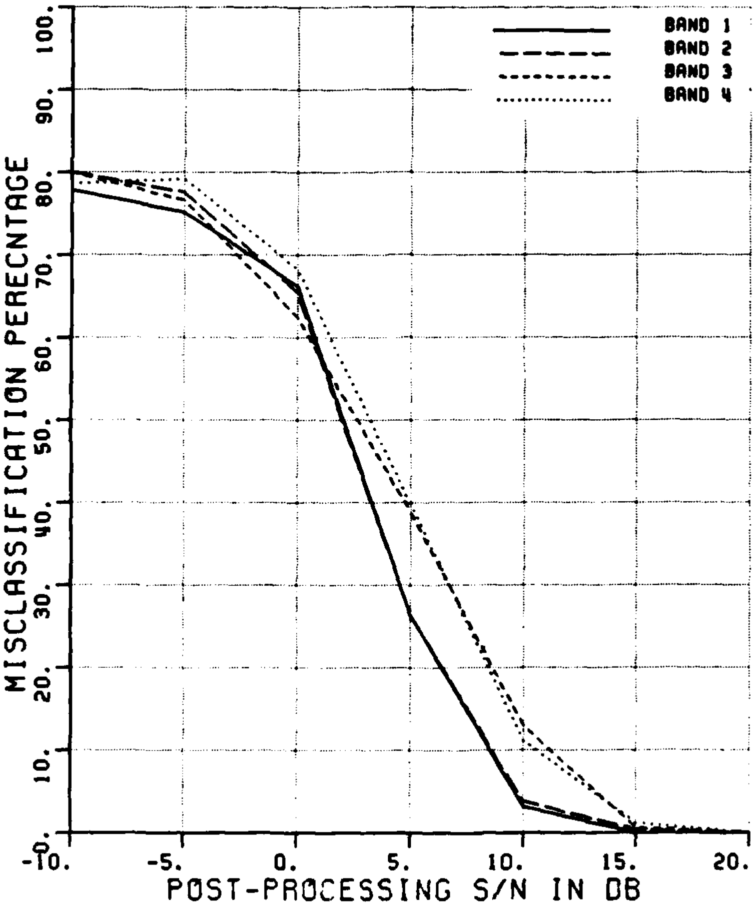

Figure A.2 Misclassification percentage versus post-processing SNR, comparing the performance of 4 sub bands in the 25-200 MHz band.

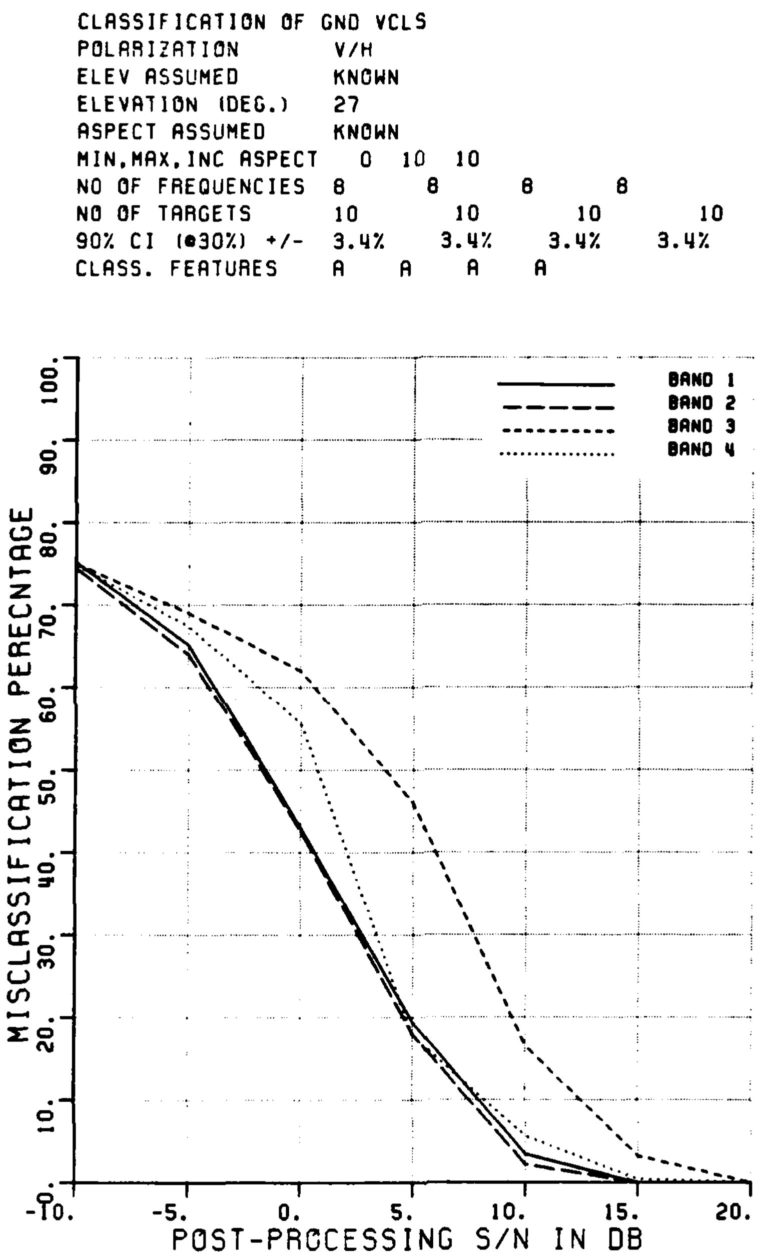

Figure A.3 Misclassification percentage versus post-processing SNR, comparing the performance of 4 sub bands in the 25-200 MHz band.

CLASSIFICATION OF GND VCLS
POLARIZATION V
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN
MIN,MAX,INC ASPECT 40 50 5
NO OF FREQUENCIES 8 8 8 8
NO OF TARGETS 15 15 15 15
90% CI (@30%) +/- 2.8% 2.8% 2.8% 2.8%
CLASS. FEATURES A A A A

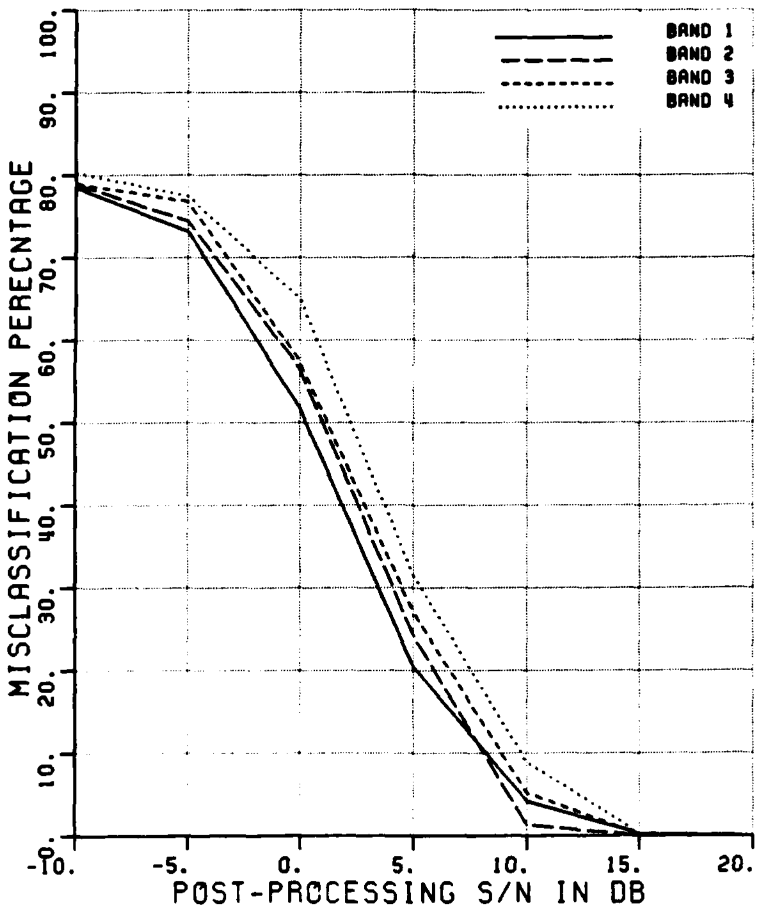

Figure A.4 Misclassification percentage versus post-processing SNR, comparing the performance of 4 sub bands in the 25-200 MHz band.

CLASSIFICATION OF GND VCLS				
POLARIZATION	H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	40 50 5			
NO OF FREQUENCIES	8	8	8	8
NO OF TARGETS	15	15	15	15
90% CI (@30%) +/-	2.8%	2.8%	2.8%	2.8%
CLASS. FEATURES	A	A	A	A

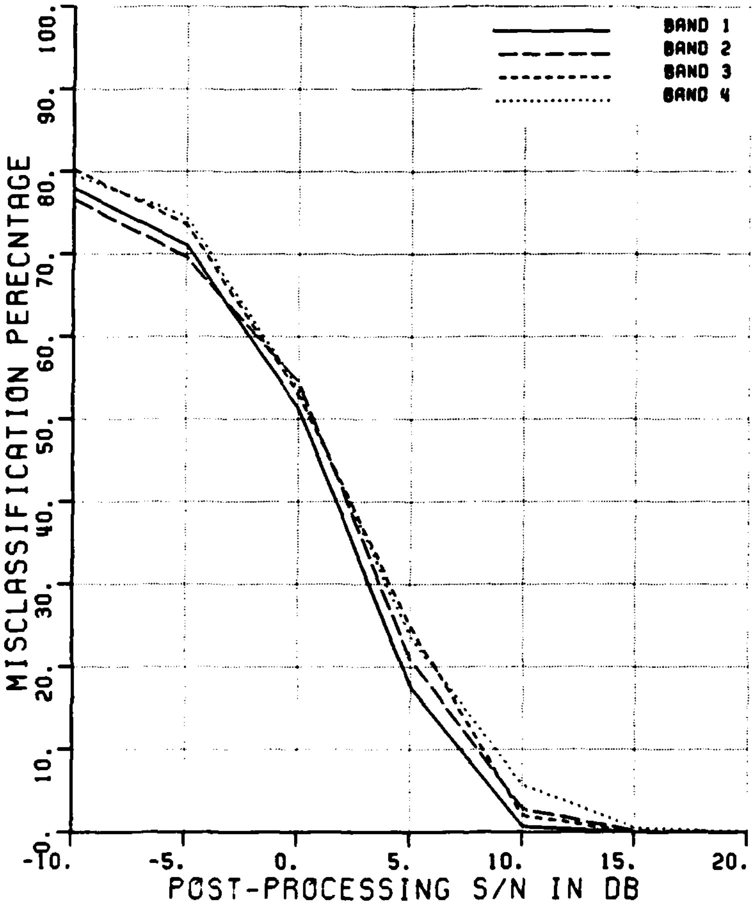

Figure A.5 Misclassification percentage versus post-processing SNR, comparing the performance of 4 sub bands in the 25-200 MHz band.

CLASSIFICATION OF GND VCLS

POLARIZATION	V/H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	40 50 5			
NO OF FREQUENCIES	8	8	8	8
NO OF TARGETS	15	15	15	15
90% CI (@30%) +/-	2.8%	2.8%	2.8%	2.8%
CLASS. FEATURES	A	A	A	A

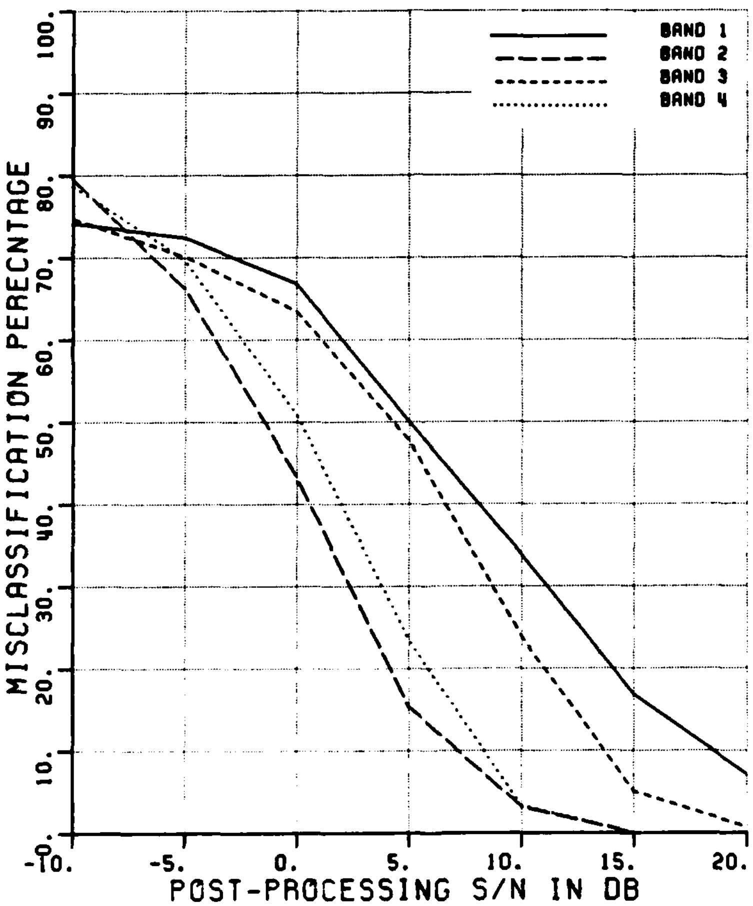

Figure A.6 Misclassification percentage versus post-processing SNR, comparing the performance of 4 sub bands in the 25-200 MHz band.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	80 90 10			
NO OF FREQUENCIES	8	8	8	8
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	A	A	A	A

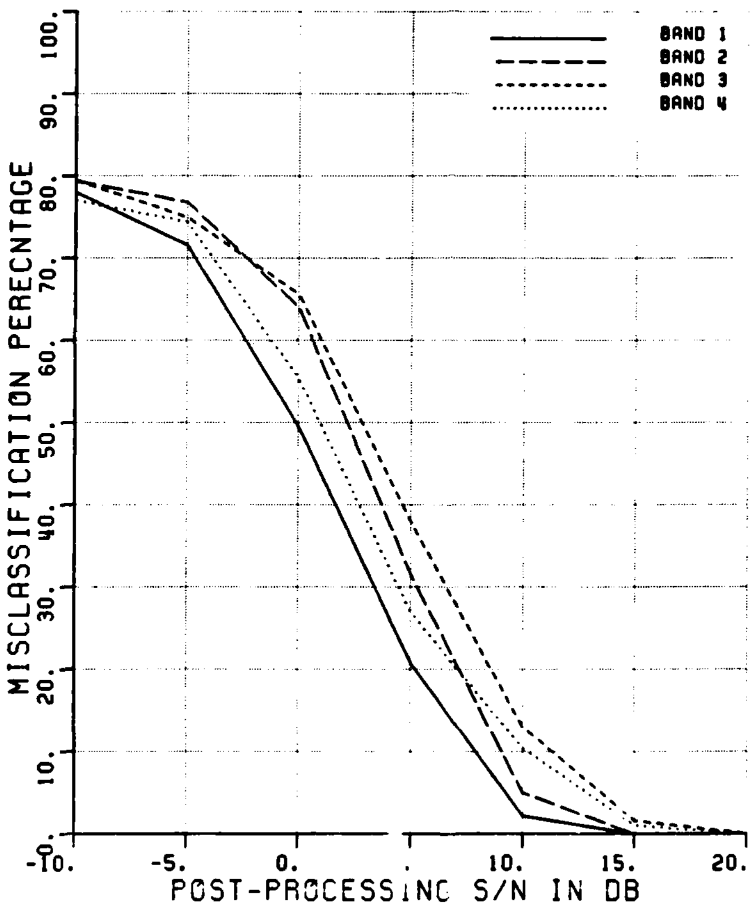

Figure A.7 Misclassification percentage versus post-processing SNR, comparing the performance of 4 sub bands in the 25-200 MHz band.

CLASSIFICATION OF GND VCLS				
POLARIZATION	H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	80 90 10			
NO OF FREQUENCIES	8	8	8	8
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	A	A	A	A

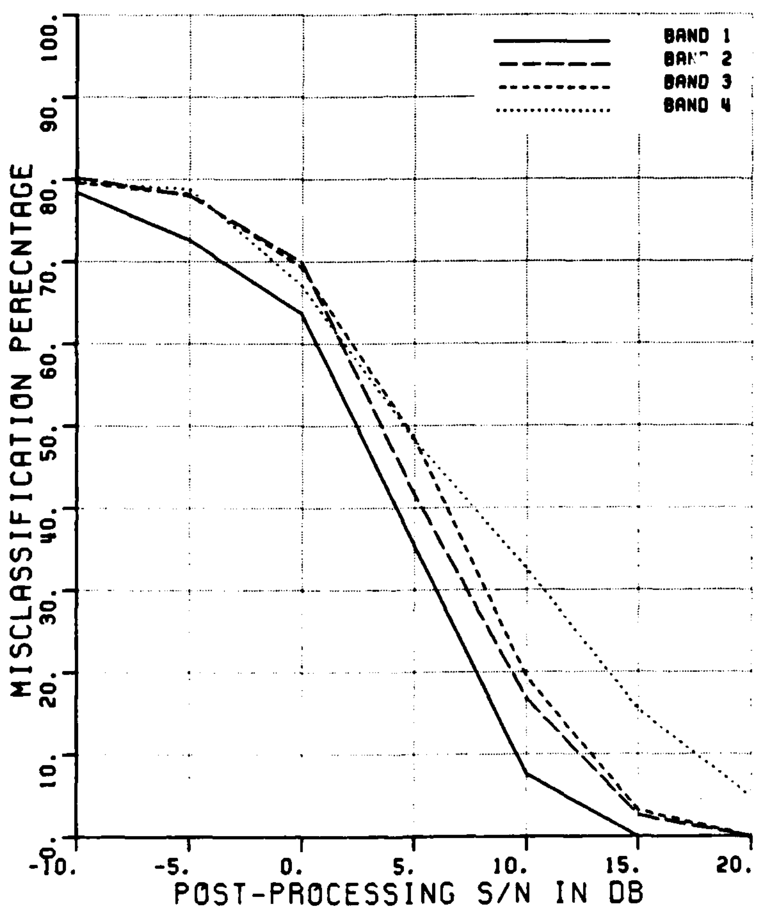

Figure A.8 Misclassification percentage versus post-processing SNR, comparing the performance of 4 sub bands in the 25-200 MHz band.

CLASSIFICATION OF GND VCLS
POLARIZATION V/H
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN
MIN,MAX,INC ASPECT 80 90 10
NO OF FREQUENCIES 8 8 8 8
NO OF TARGETS 10 10 10 10
90% CI (@30%) +/- 3.4% 3.4% 3.4% 3.4%
CLASS. FEATURES A A A A

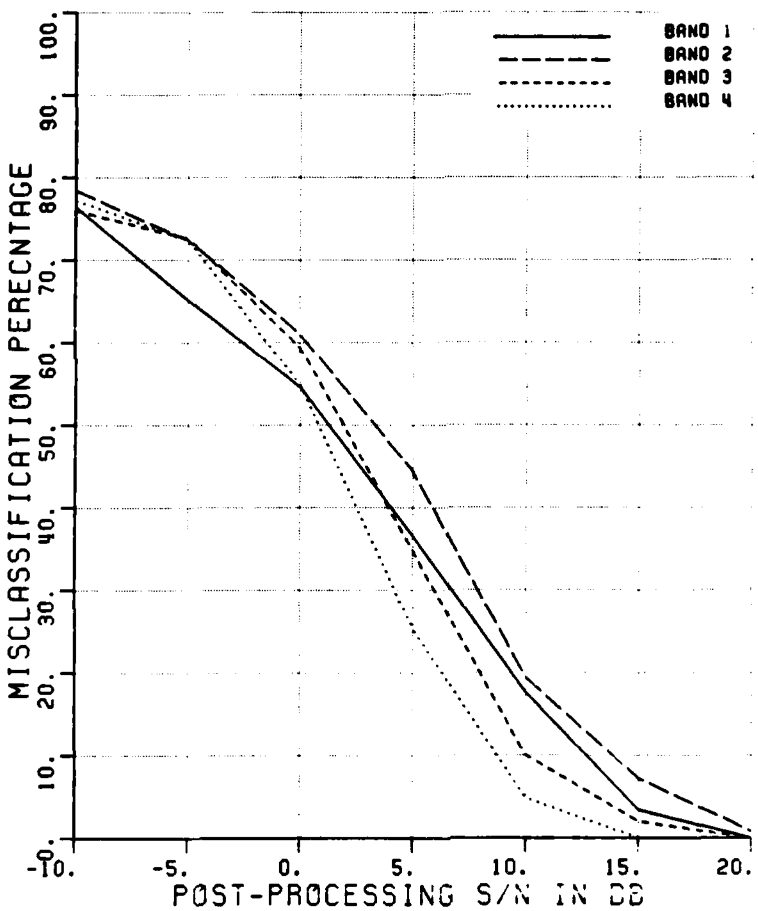

Figure A.9 Misclassification percentage versus post-processing SNR, comparing the performance of 4 sub bands in the 25-200 MHz band.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	0 10 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	A	A	A	A

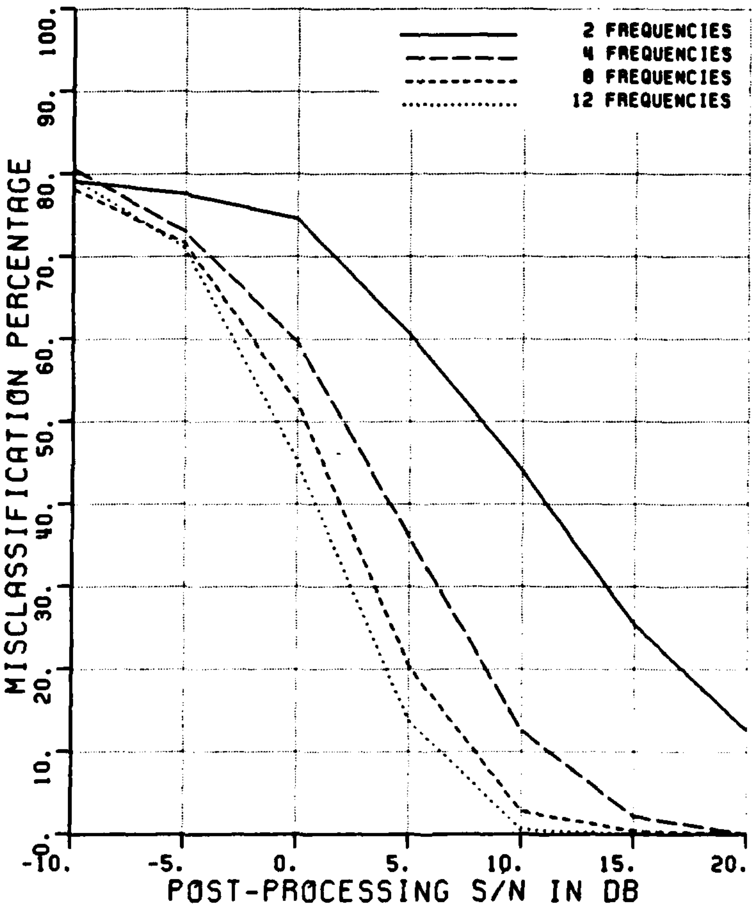

Figure A.10 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	0 10 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	A	A	A	A

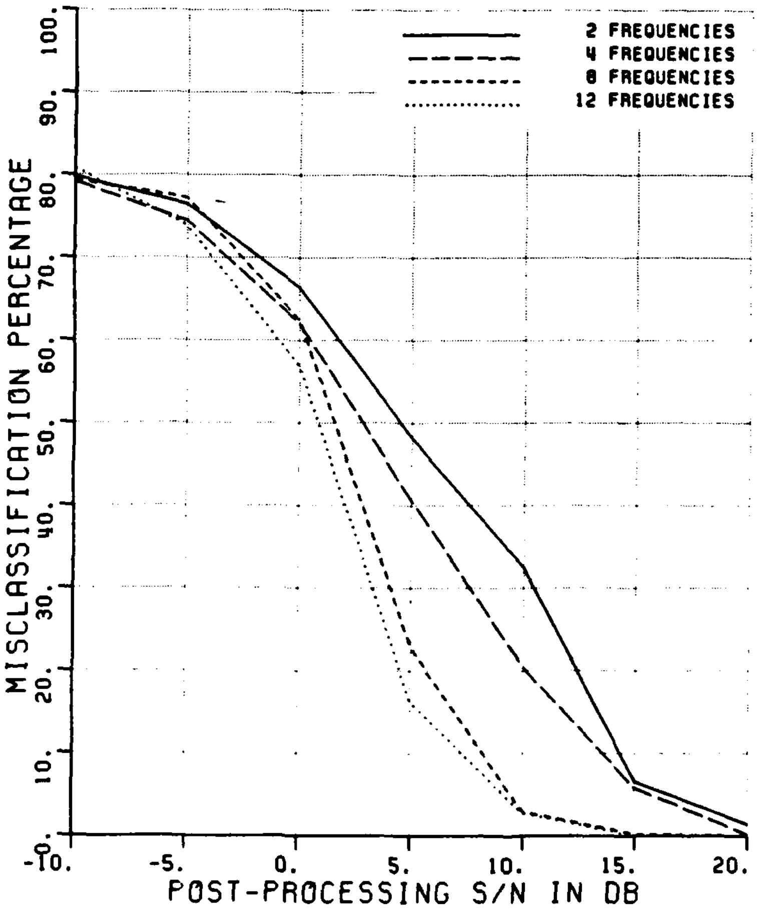

Figure A.11 Misclassification percentage versus post-processing SNR, comparing the performance of 4 value of NF.

CLASSIFICATION OF GND VCLS
POLARIZATION V/H
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN
MIN,MAX,INC ASPECT 0 10 10
NO OF FREQUENCIES 2 4 8 12
NO OF TARGETS 10 10 10 10
90% CI (@30%) +/- 3.4% 3.4% 3.4% 3.4%
CLASS. FEATURES A A A A

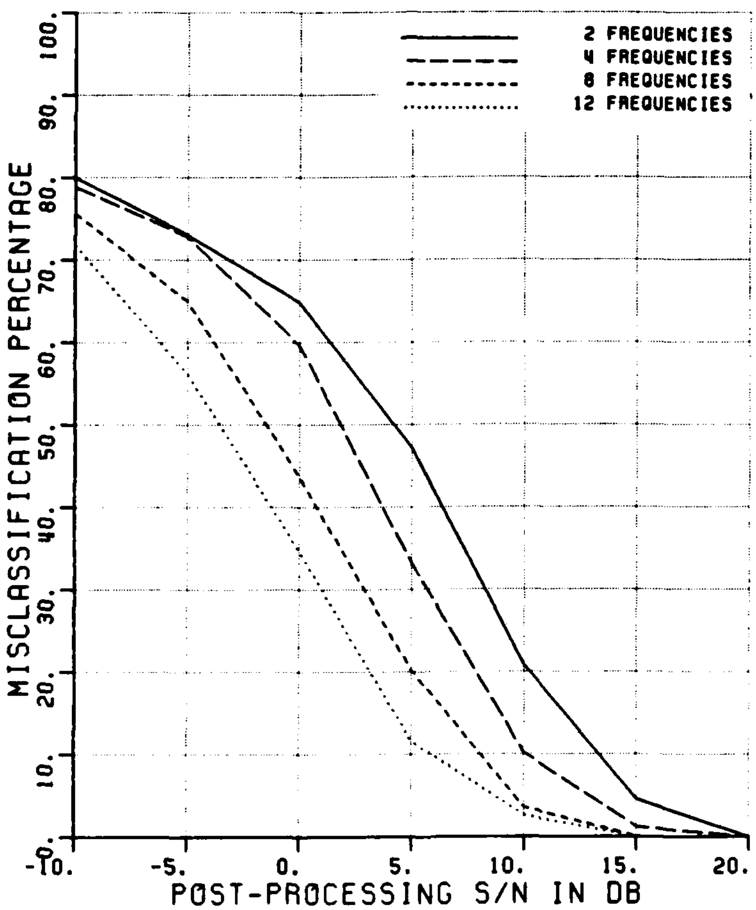

Figure A.12 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	40 50 5			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	15	15	15	15
90% CI (@30%) +/-	2.8%	2.8%	2.8%	2.8%
CLASS. FEATURES	A	A	A	A

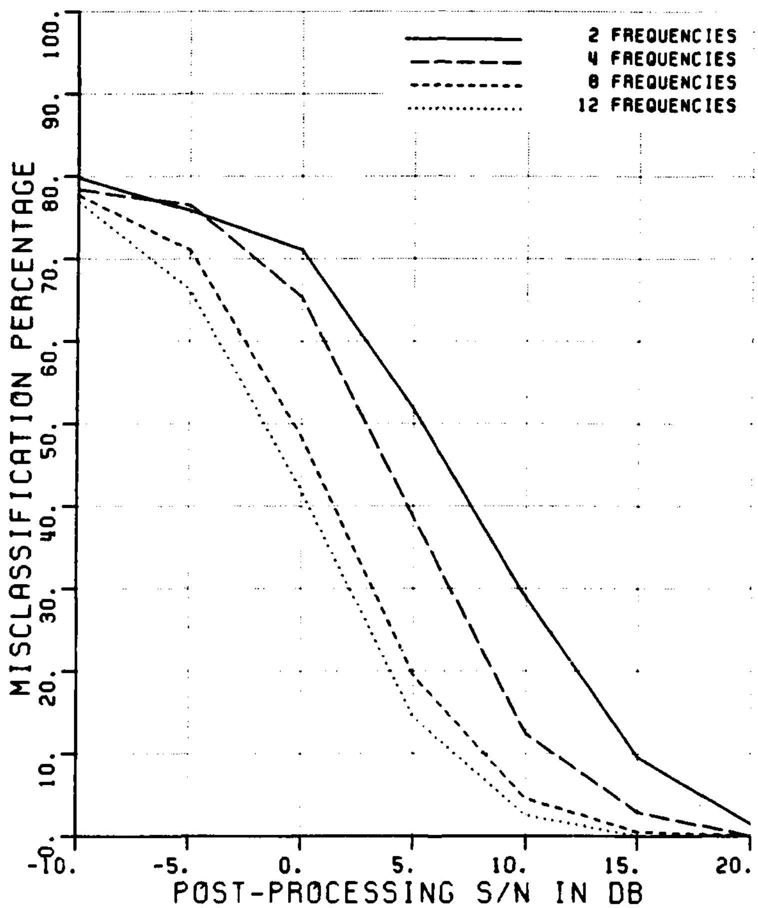

Figure A.13 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	40 50 5			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	15	15	15	15
90% CI (@30%) +/-	2.8%	2.8%	2.8%	2.8%
CLASS. FEATURES	A	A	A	A

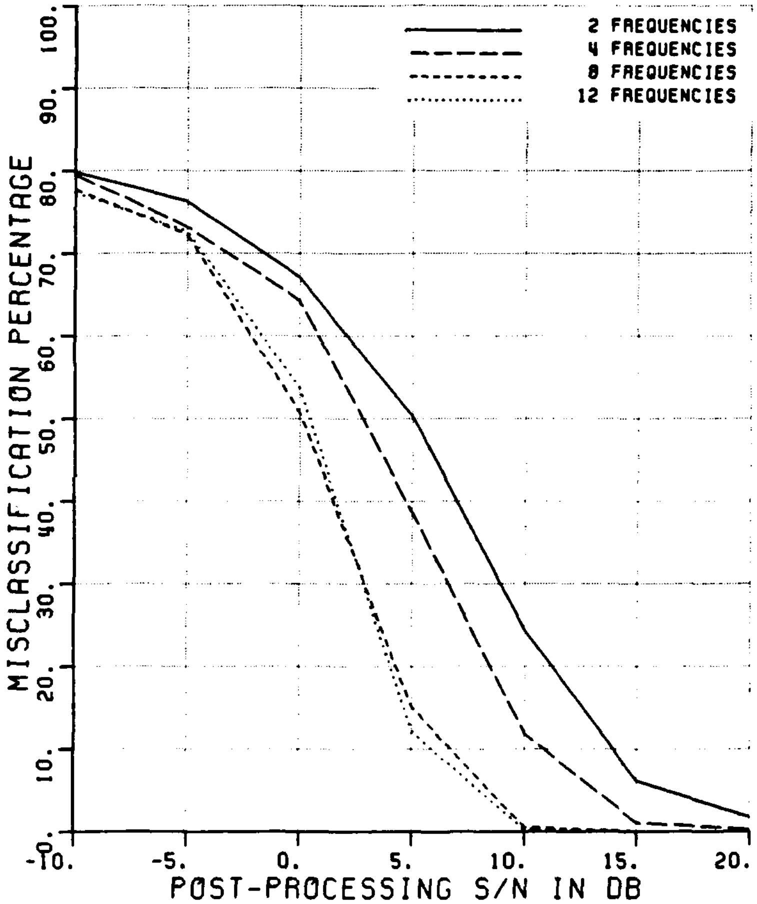

Figure A.14 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V/H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	40	50	5	
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	15	15	15	15
90% CI (@30%) +/-	2.8%	2.8%	2.8%	2.8%
CLASS. FEATURES	A	A	A	A

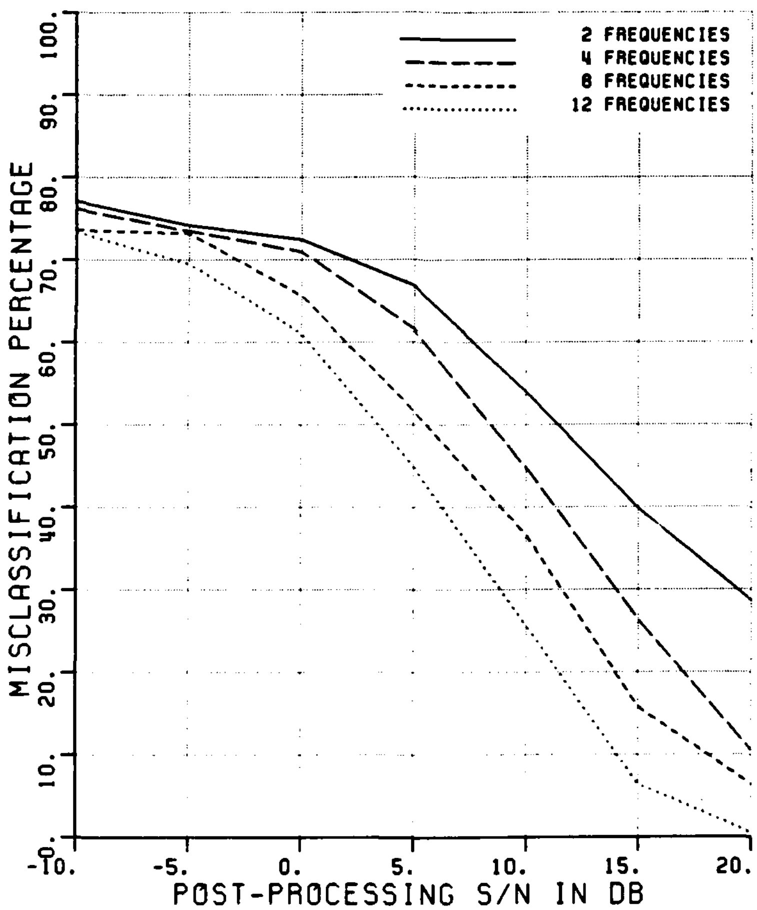

Figure A.15 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	80 90 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	A	A	A	A

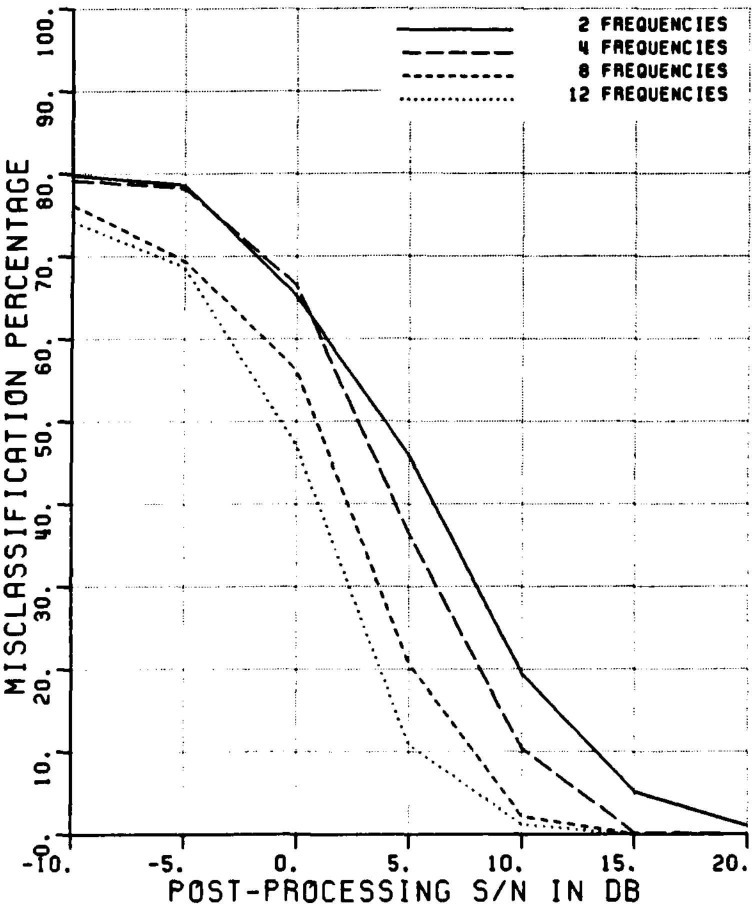

Figure A.16 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	80 90 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	A	A	A	A

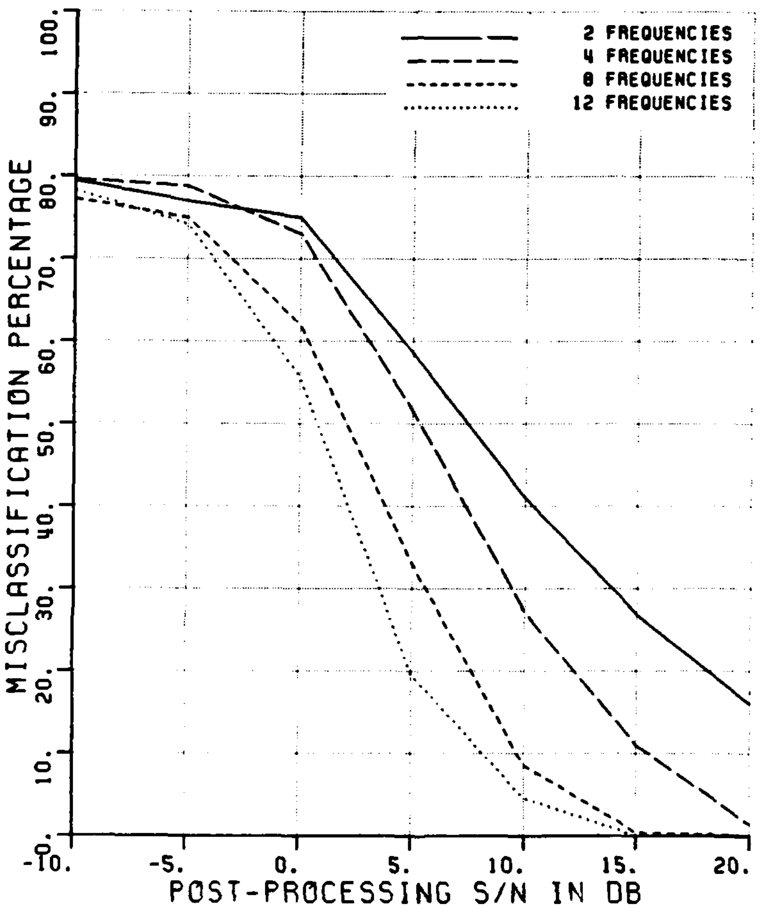

Figure A.17 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS
POLARIZATION V/H
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN
MIN,MAX,INC ASPECT 80 90 10

NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	A	A	A	A

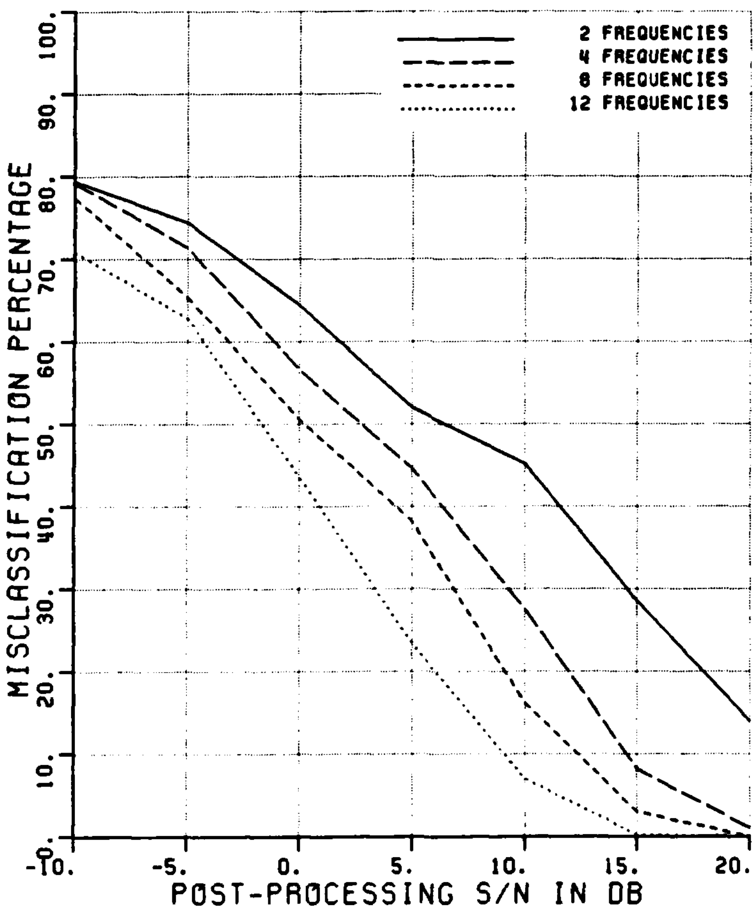

Figure A.18 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	0 10 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	A&W	A&W	A&W	A&W

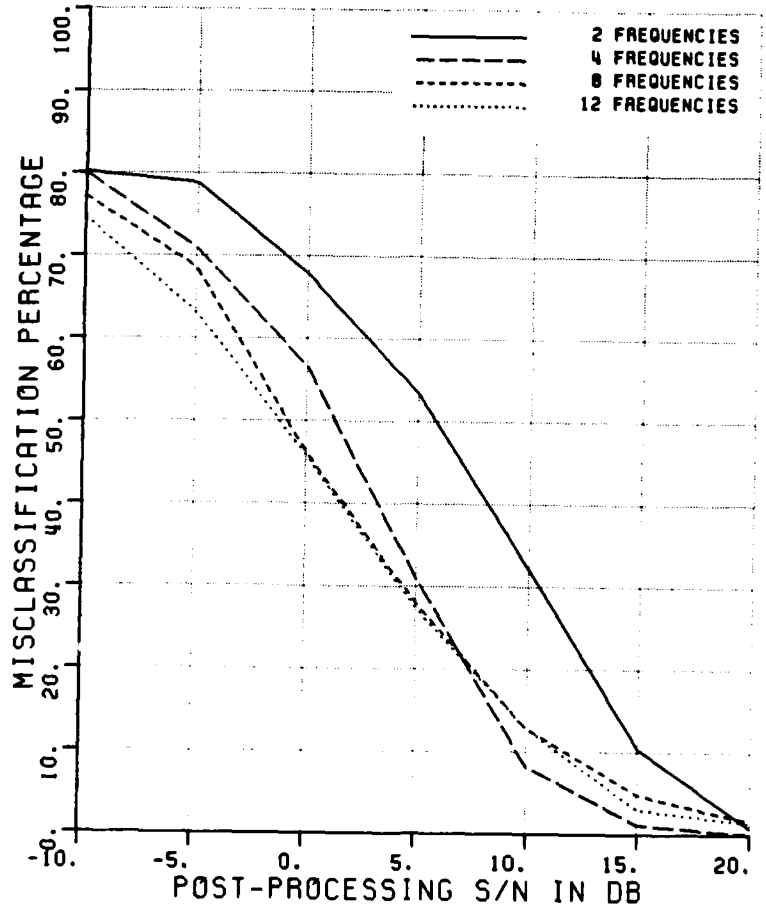

Figure A.19 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	0 10 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	A&W	A&W	A&W	A&W

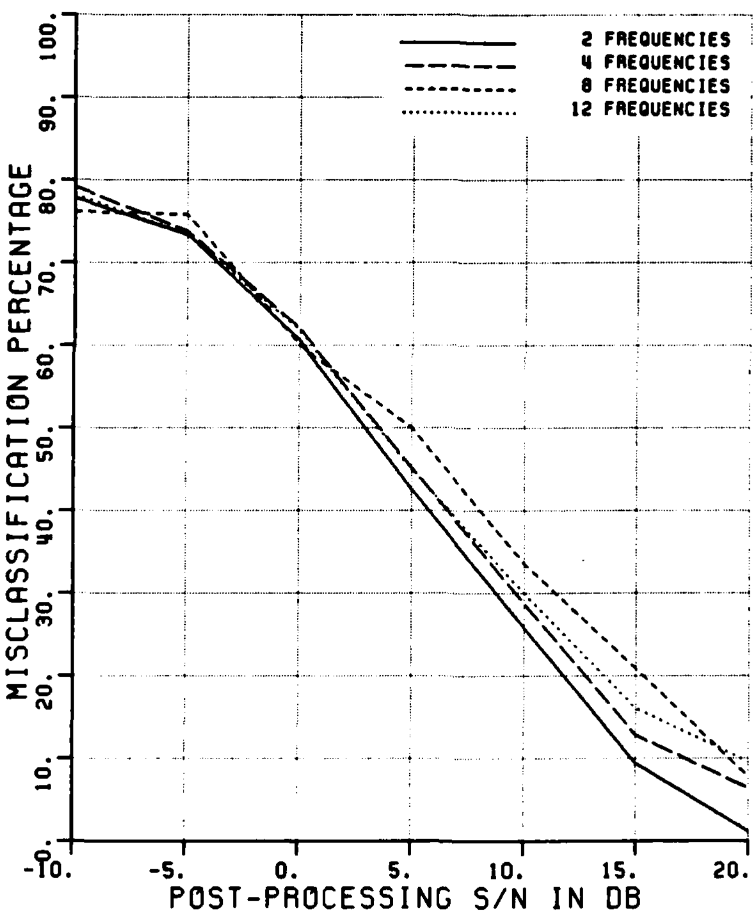

Figure A.20 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V/H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	0 10 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	A&W	A&W	A&W	A&W

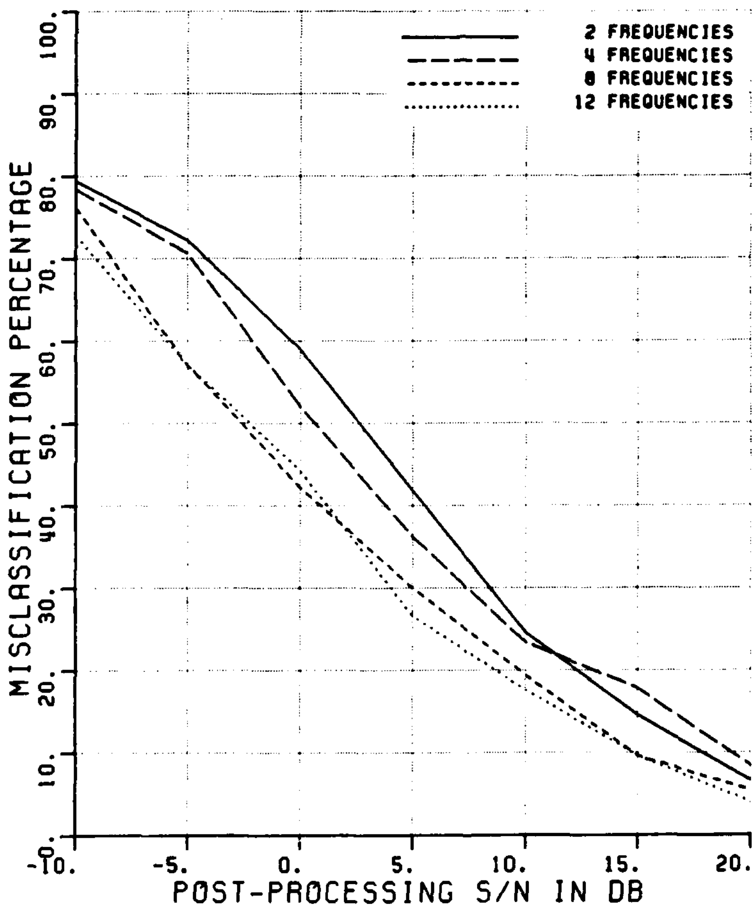

Figure A.21 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	40 50 5			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	15	15	15	15
90% CI (@30%) +/-	2.8%	2.8%	2.8%	2.8%
CLASS. FEATURES	A&W	A&W	A&W	A&W

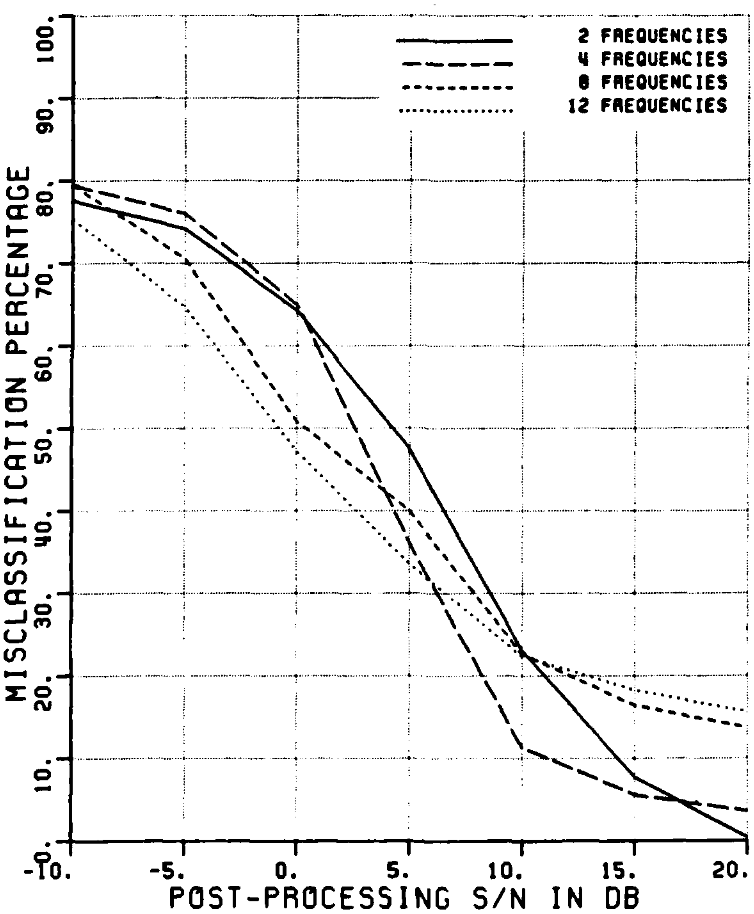

Figure A.22 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	40 50 5			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	15	15	15	15
90% CI (@30%) +/-	2.8%	2.8%	2.8%	2.8%
CLASS. FEATURES	A&W	A&W	A&W	A&W

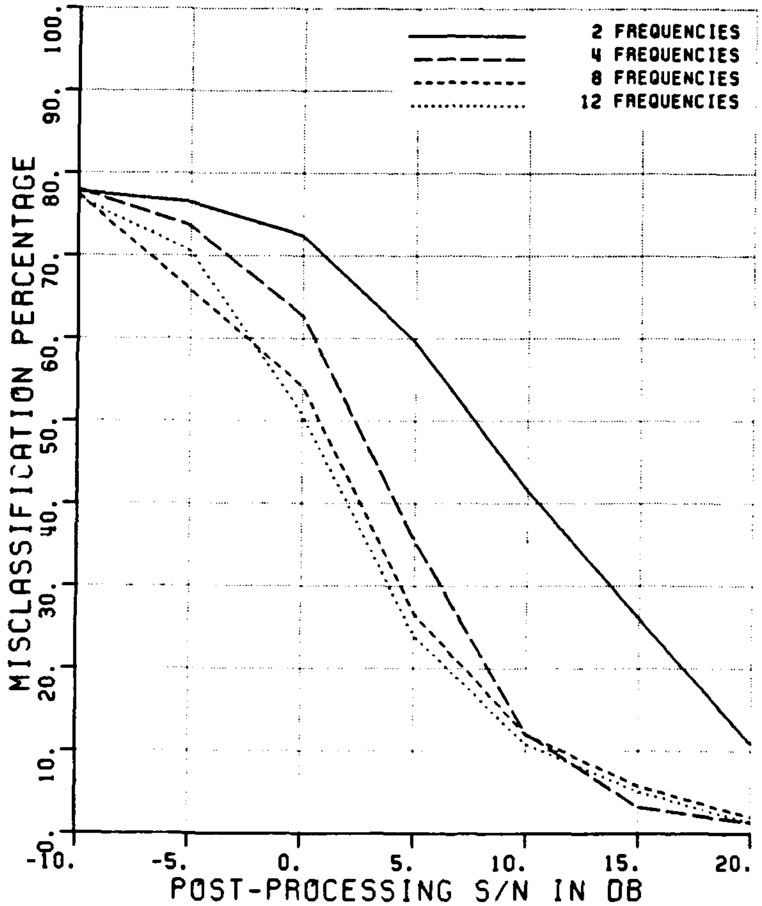

Figure A.23 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V/H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	40 50 5			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	15	15	15	15
90% CI (@30%) +/-	2.8%	2.8%	2.8%	2.8%
CLASS. FEATURES	A&W	A&W	A&W	A&W

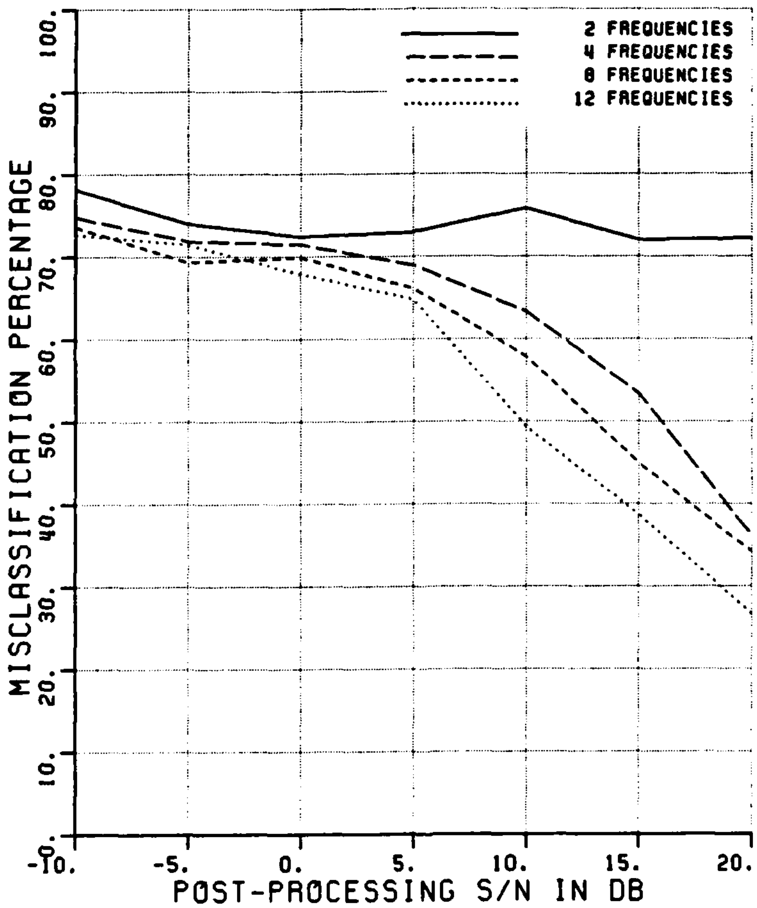

Figure A.24 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	80 90 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	A&W	A&W	A&W	A&W

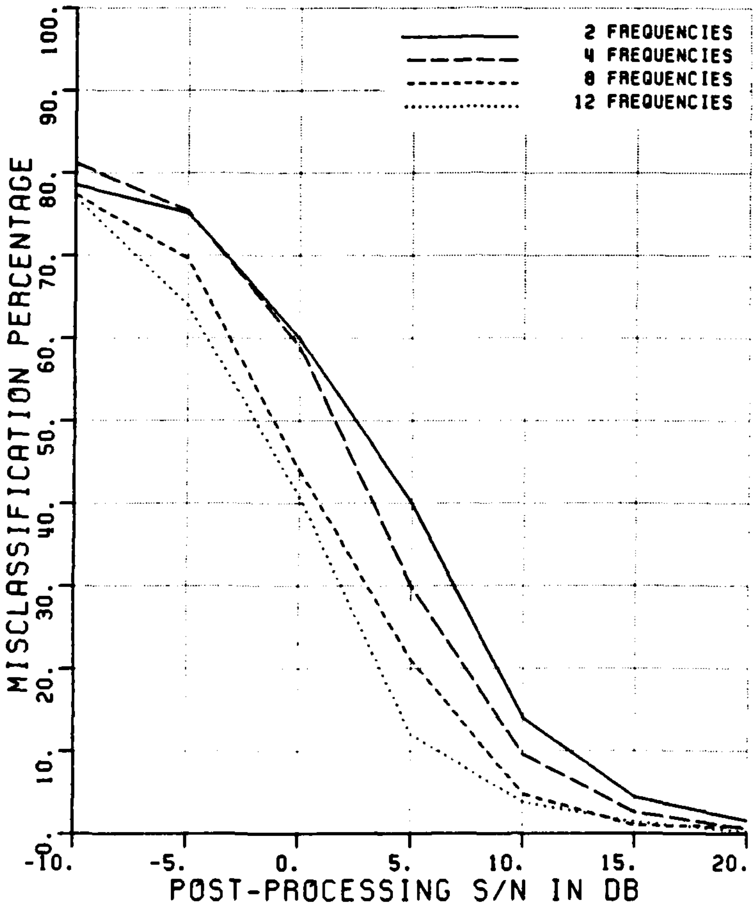

Figure A.25 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	80 90 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	A&W	A&W	A&W	A&W

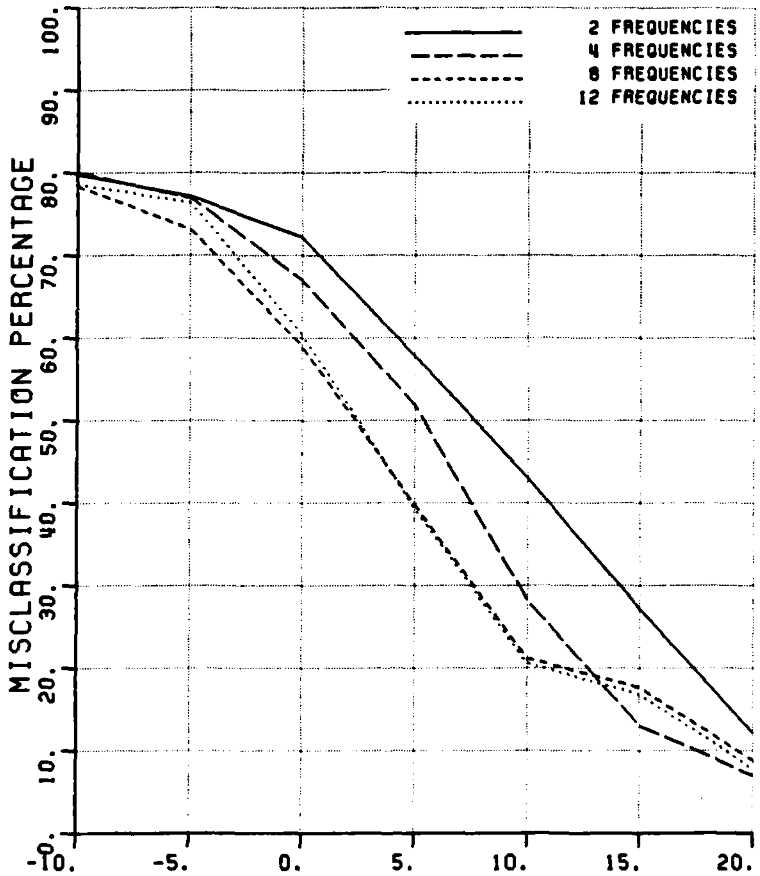

Figure A.26 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V/H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	80 90 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	A&W	A&W	A&W	A&W

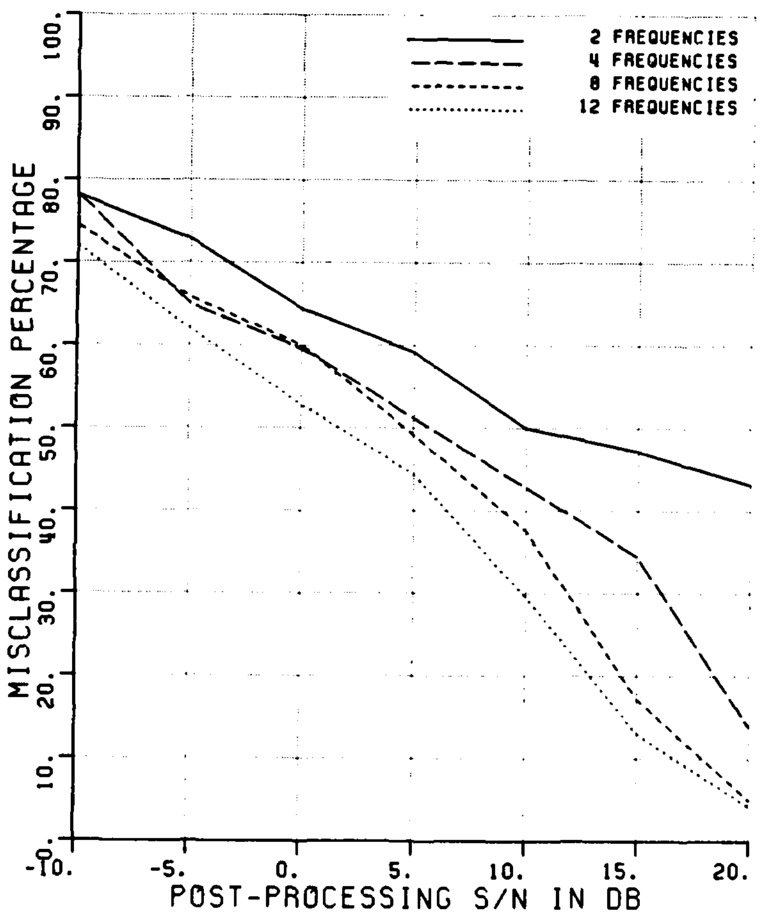

Figure A.27 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS

POLARIZATION	V			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	0 10 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	W	W	W	W

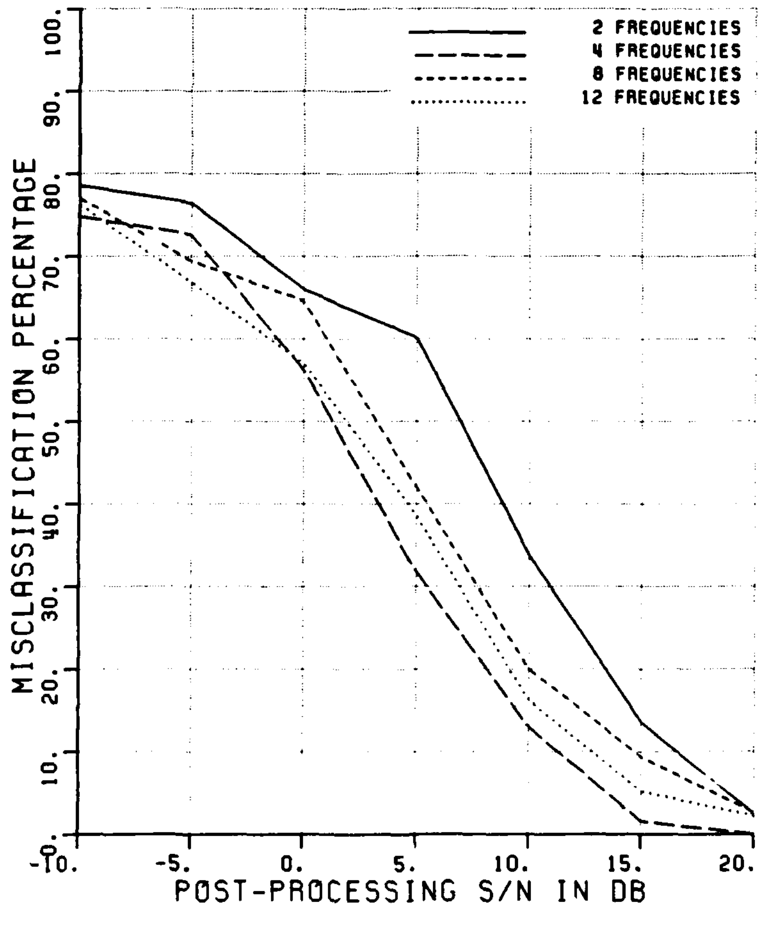

Figure A.28 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

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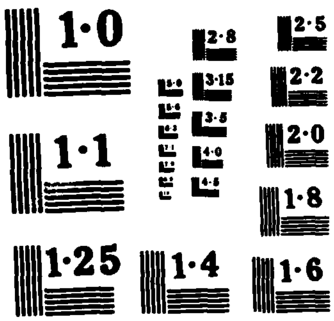

NATIONAL BUREAU OF STANDARDS
MICROCOPY RESOLUTION TEST CHART

CLASSIFICATION OF GND VCLS
POLARIZATION H
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN
MIN,MAX,INC ASPECT 0 10 10
NO OF FREQUENCIES 2 4 8 12
NO OF TARGETS 10 10 10 10
90% CI (@30%) +/- 3.4% 3.4% 3.4% 3.4%
CLASS. FEATURES W W W W

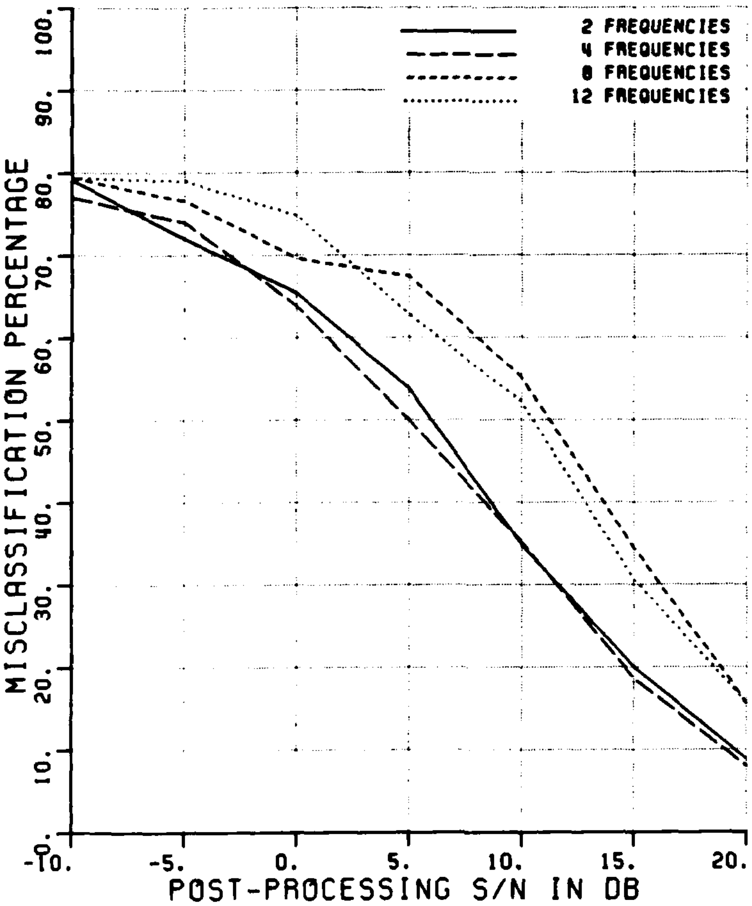

Figure A.29 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS
POLARIZATION V/H
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN
MIN,MAX,INC ASPECT 0 10 10
NO OF FREQUENCIES 2 4 8 12
NO OF TARGETS 10 10 10 10
90% CI (@30%) +/- 3.4% 3.4% 3.4% 3.4%
CLASS. FEATURES W W W W

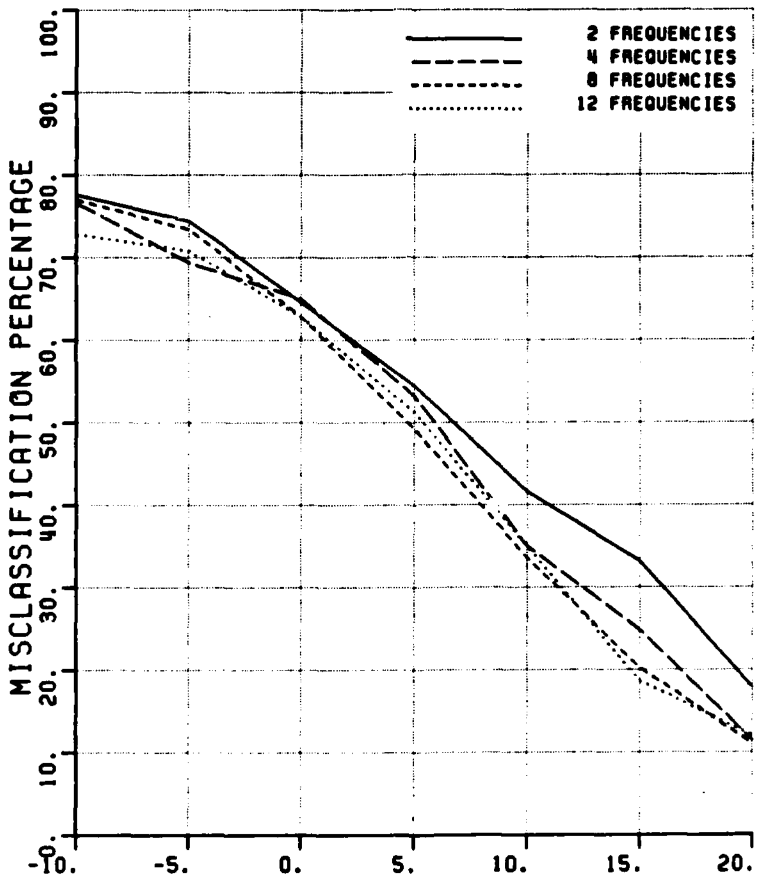

Figure A.30 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	40 50 5			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	15	15	15	15
90% CI (@30%) +/-	2.8%	2.8%	2.8%	2.8%
CLASS. FEATURES	W	W	W	W

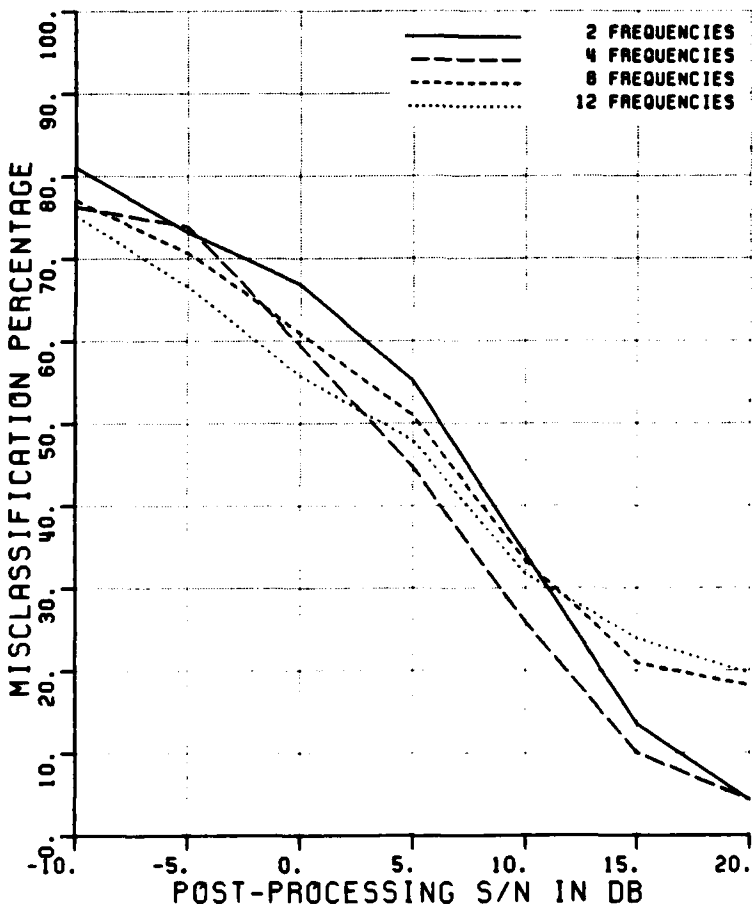

Figure A.31 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	40 50 5			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	15	15	15	15
90% CI (@30%) +/-	2.8%	2.8%	2.8%	2.8%
CLASS. FEATURES	W	W	W	W

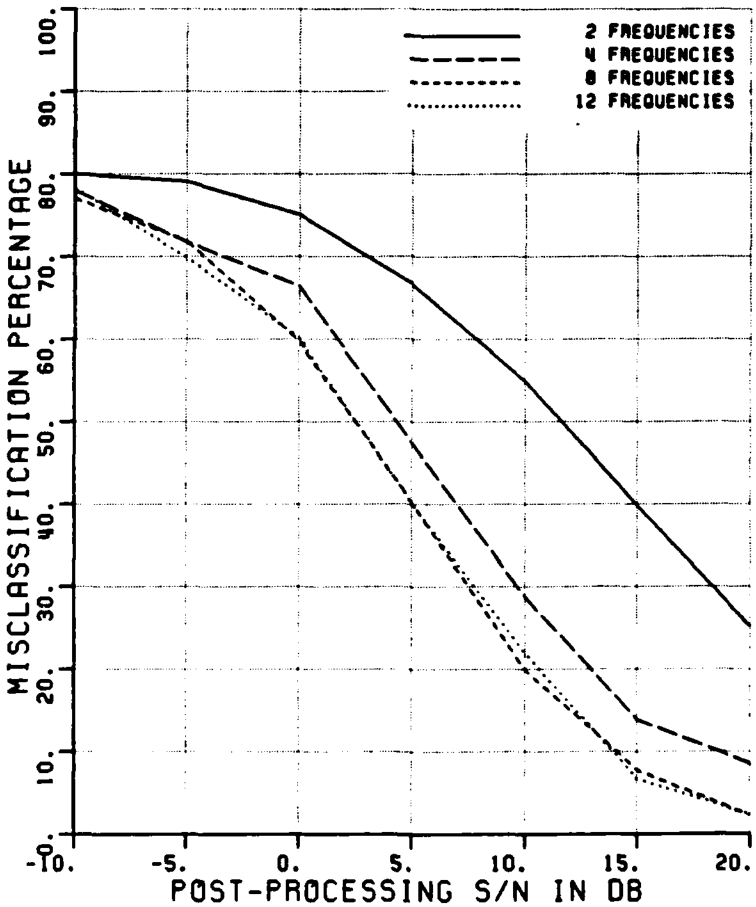

Figure A.32 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V/H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	40 50 5			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	15	15	15	15
90% CI (@30%) +/-	2.8%	2.8%	2.8%	2.8%
CLASS. FEATURES	W	W	W	W

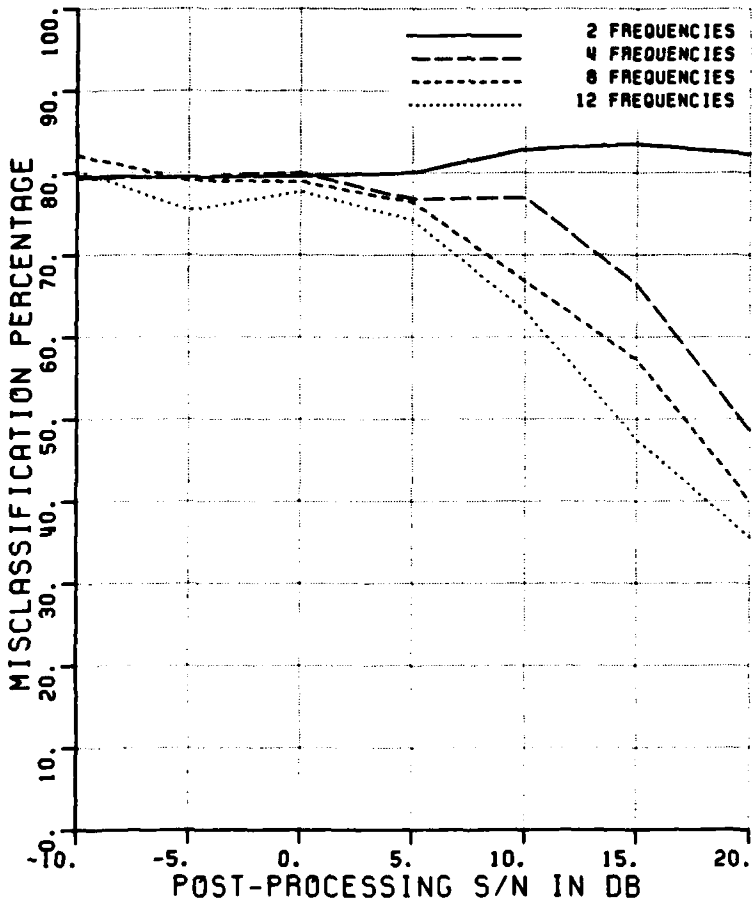

Figure A.33 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	80 90 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	W	W	W	W

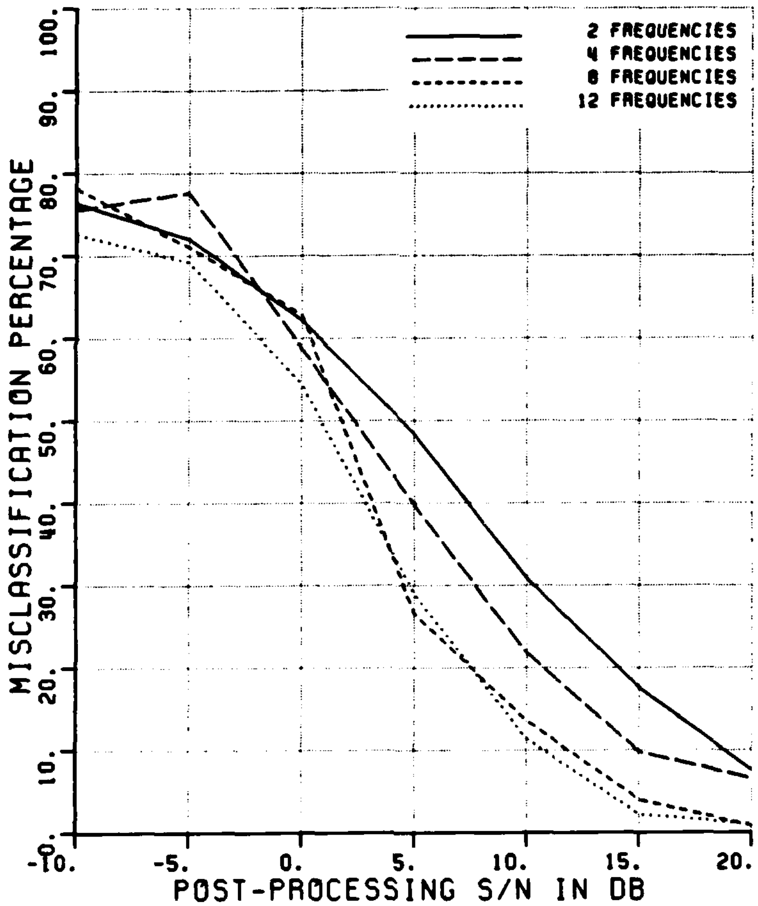

Figure A.34 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	80 90 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	W	W	W	W

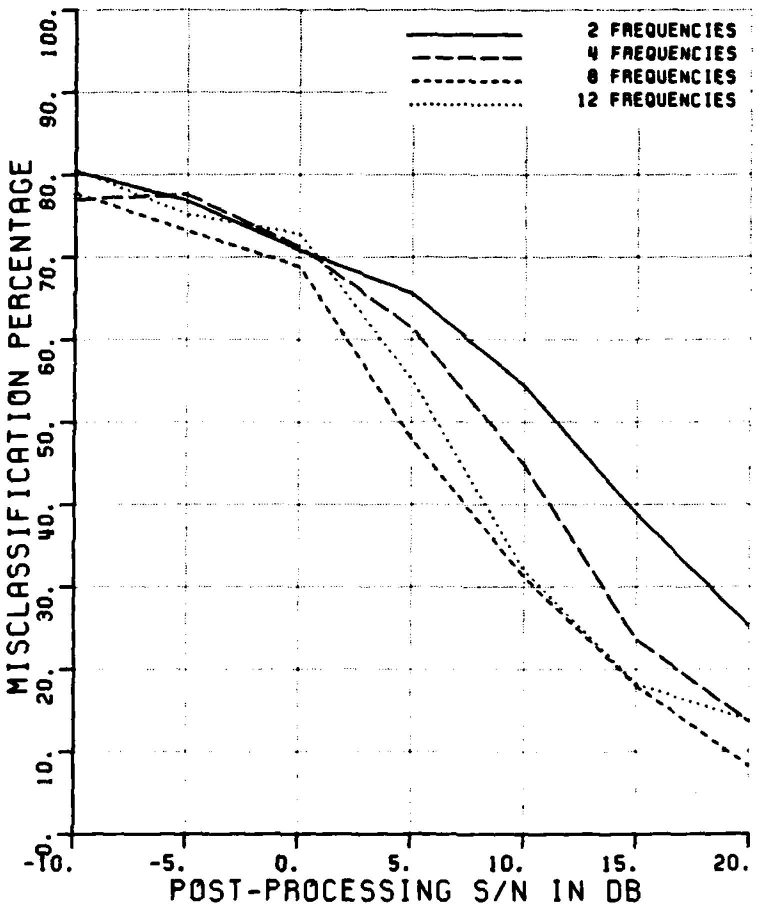

Figure A.35 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V/H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	80 90 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	W	W	W	W

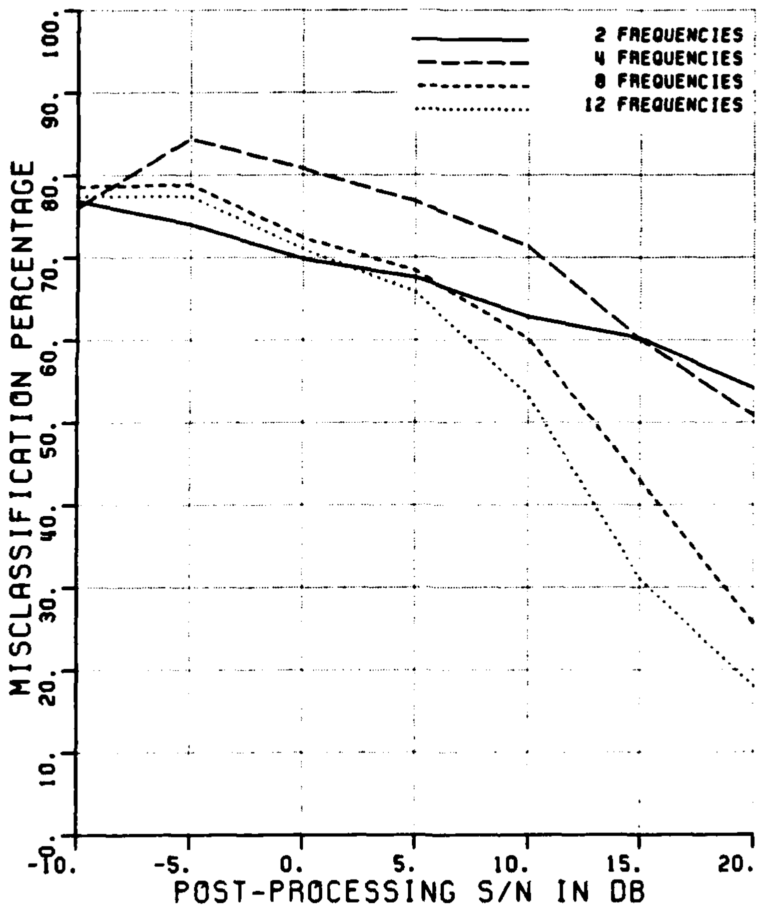

Figure A.36 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS
POLARIZATION V
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN
MIN,MAX,INC ASPECT 0 10 10
NO OF FREQUENCIES 2 4 8 12
NO OF TARGETS 10 10 10 10
90% CI (@30%) +/- 3.4% 3.4% 3.4% 3.4%
CLASS. FEATURES T T T T

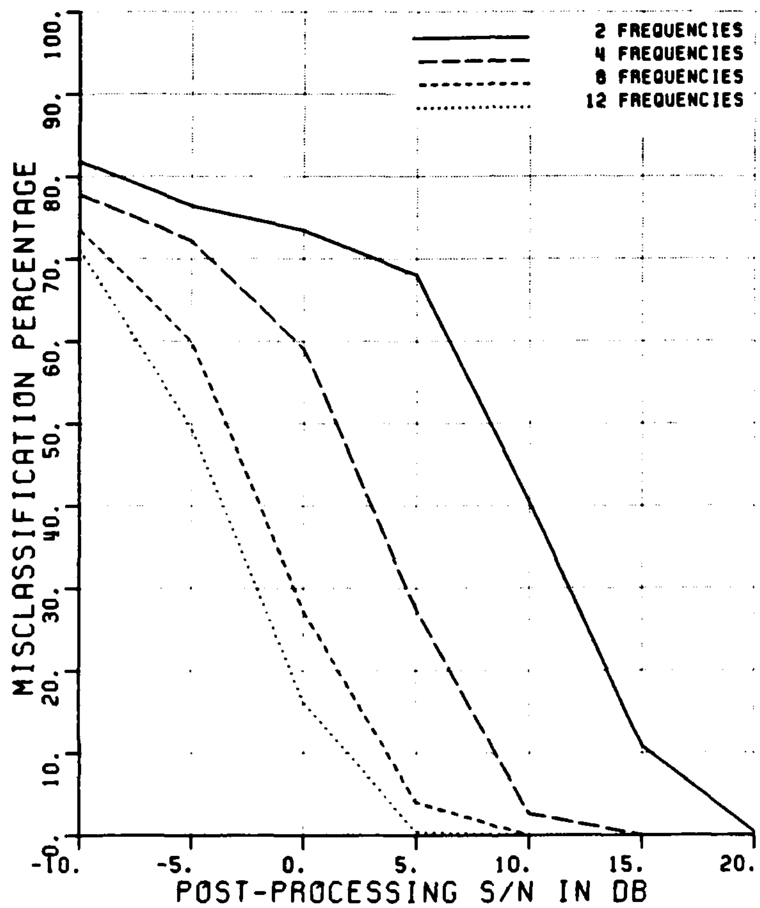

Figure A.37 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	0 10 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	T	T	T	T

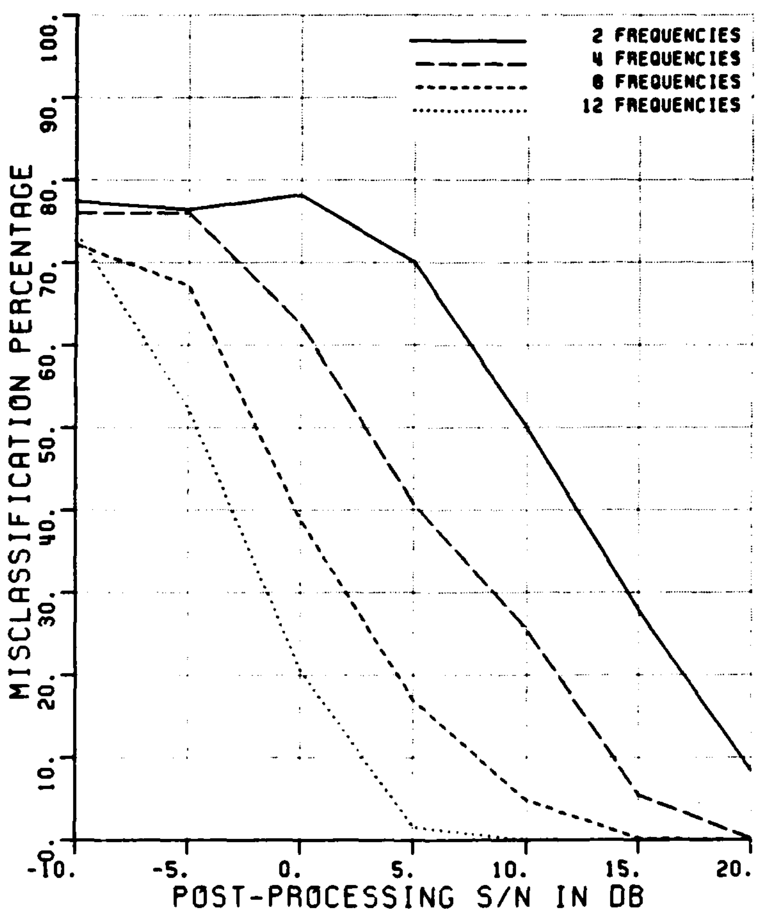

Figure A.38 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V/H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	0 10 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	T	T	T	T

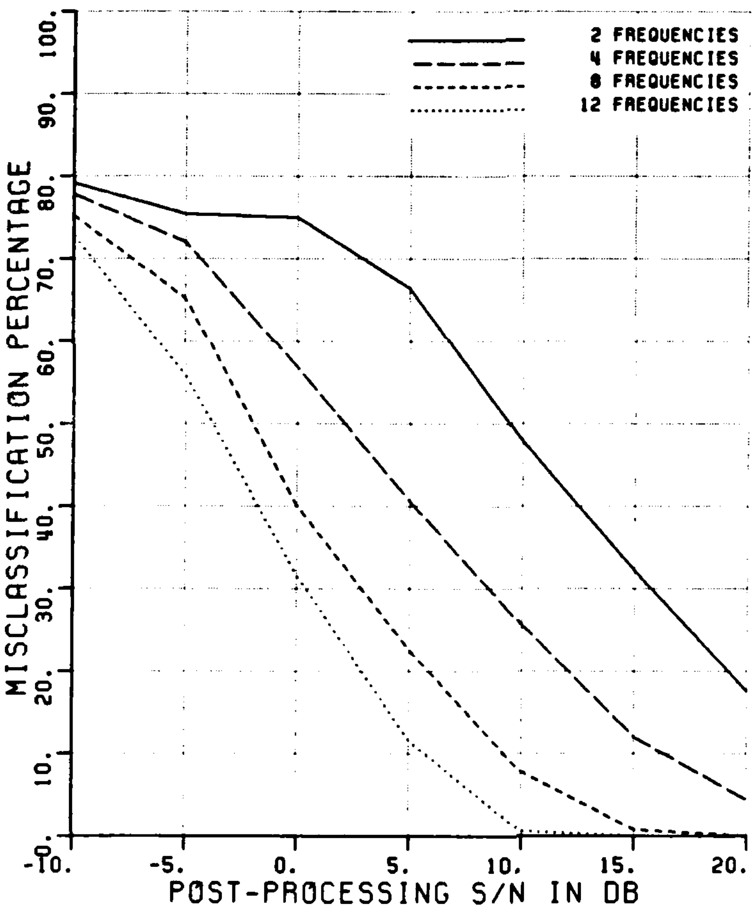

Figure A.39 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

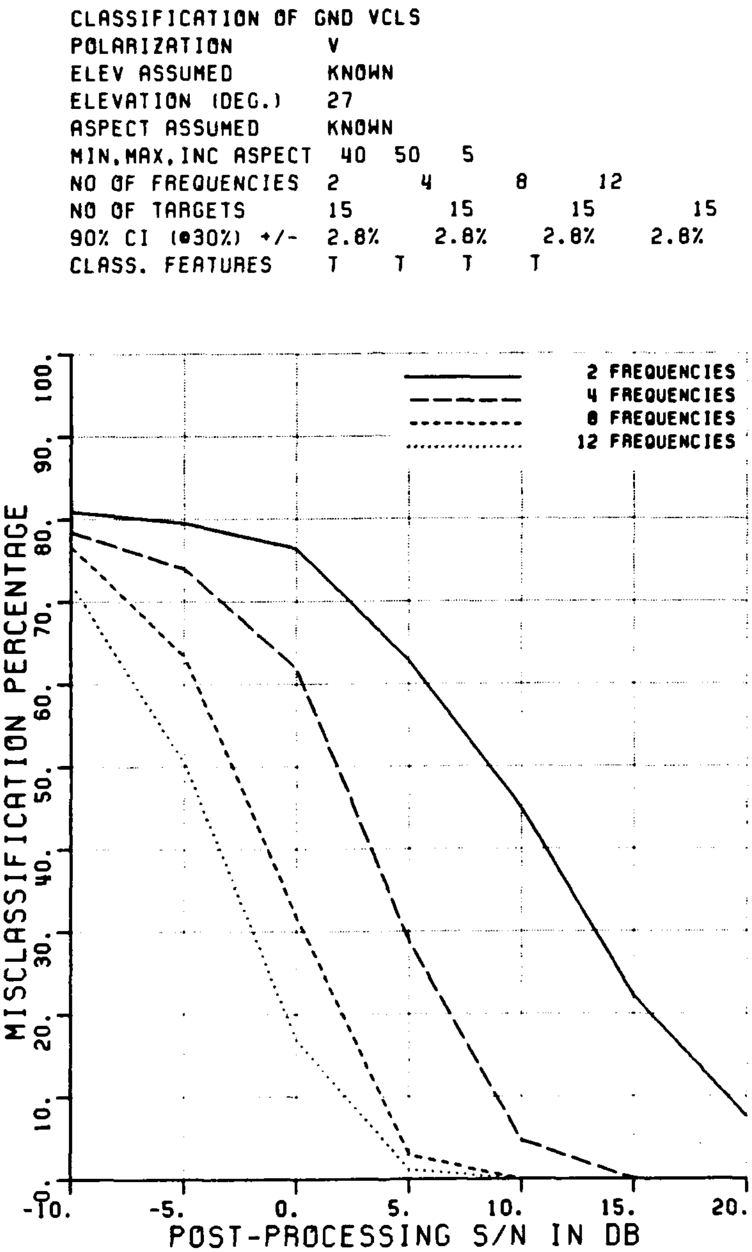

Figure A.40 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS
POLARIZATION H
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN
MIN,MAX,INC ASPECT 40 50 5
NO OF FREQUENCIES 2 4 8 12
NO OF TARGETS 15 15 15 15
90% CI (@30%) +/- 2.8% 2.8% 2.8% 2.8%
CLASS. FEATURES T T T T

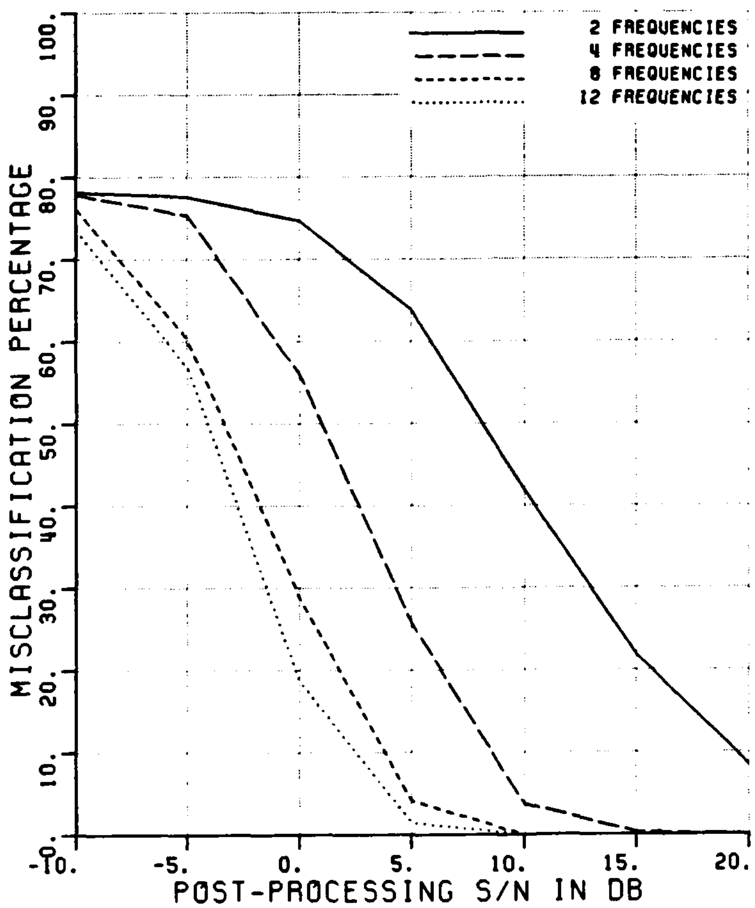

Figure A.41 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS
POLARIZATION V/H
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN
MIN,MAX,INC ASPECT 40 50 5
NO OF FREQUENCIES 2 4 8 12
NO OF TARGETS 15 15 15 15
90% CI (@30%) +/- 2.8% 2.8% 2.8% 2.8%
CLASS. FEATURES T T T T

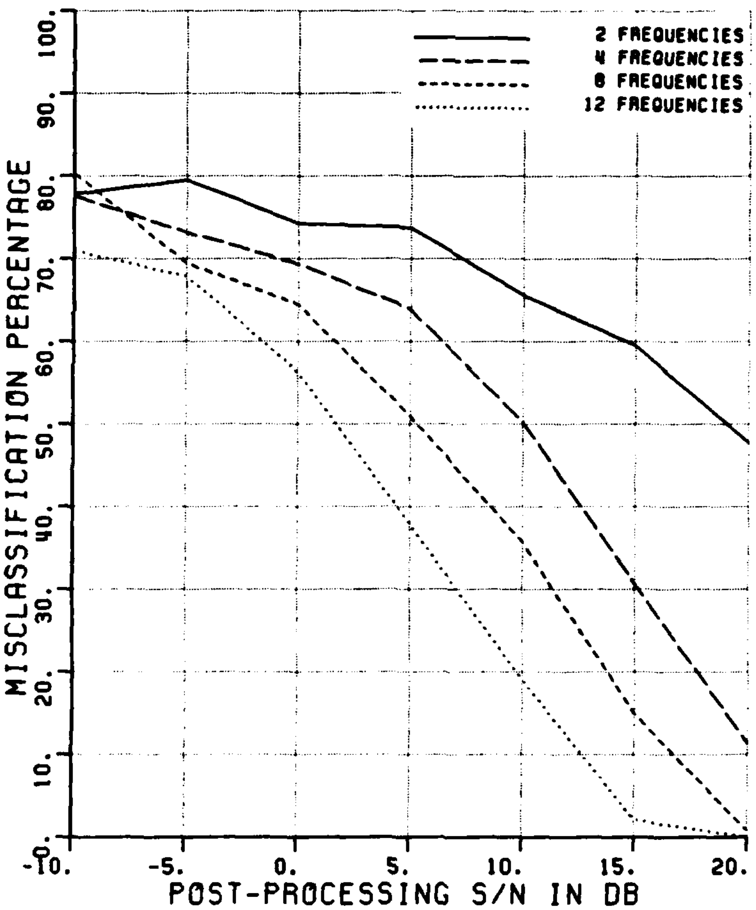

Figure A.42 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	80 90 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	T	T	T	T

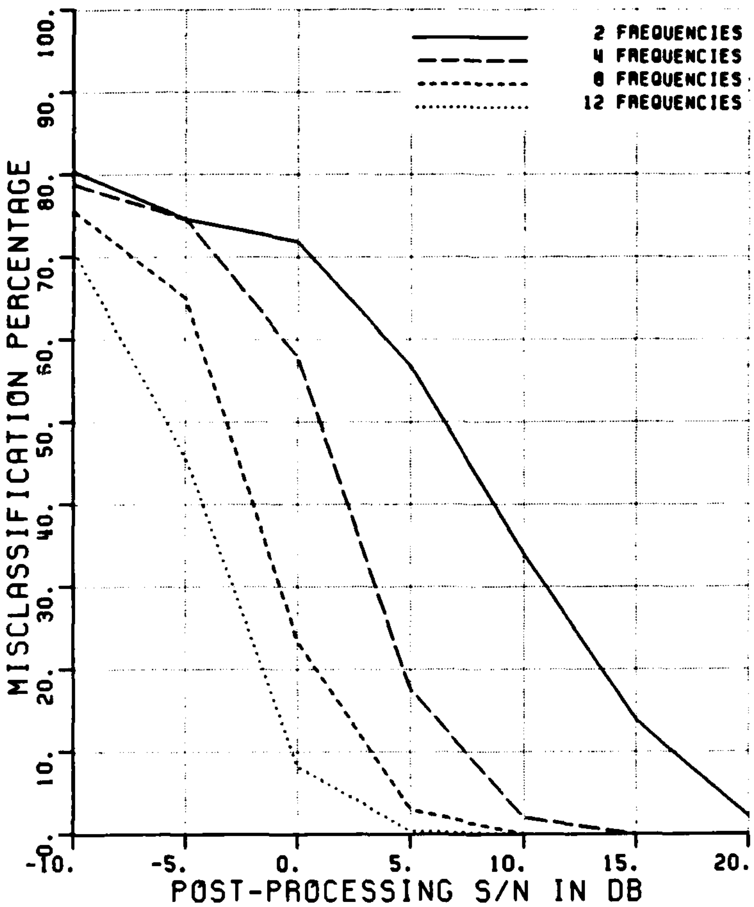

Figure A.43 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS

POLARIZATION	H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	80 90 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	T	T	T	T

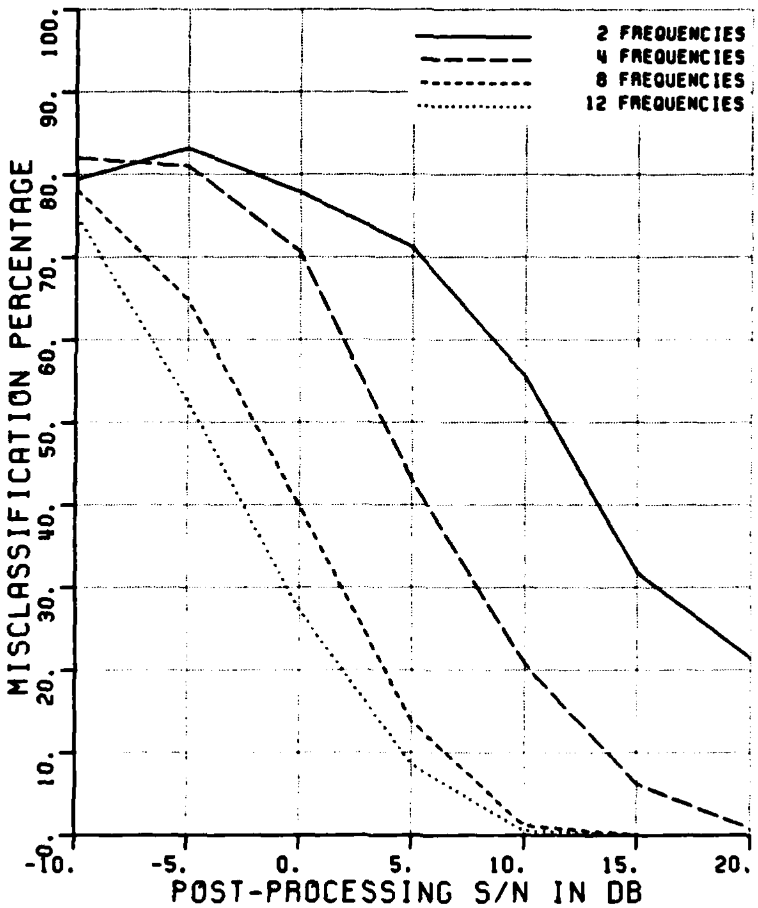

Figure A.44 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS				
POLARIZATION	V/H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN			
MIN,MAX,INC ASPECT	80 90 10			
NO OF FREQUENCIES	2	4	8	12
NO OF TARGETS	10	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%	3.4%
CLASS. FEATURES	T	T	T	T

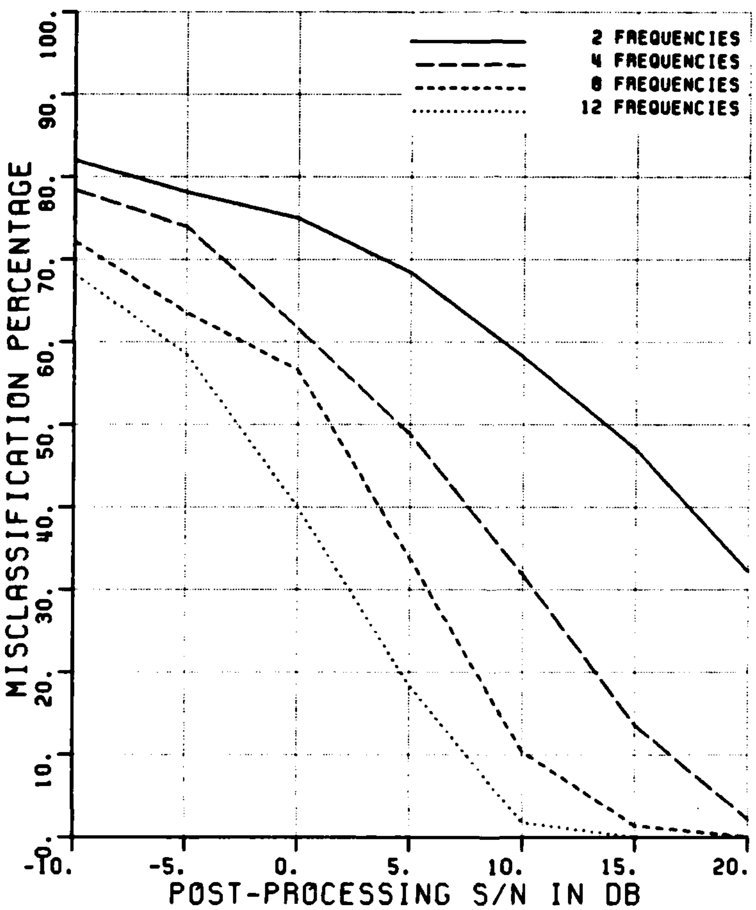

Figure A.45 Misclassification percentage versus post-processing SNR, comparing the performance of 4 values of NF.

CLASSIFICATION OF GND VCLS			
POLARIZATION	V	H	V/H
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN		
MIN,MAX,INC ASPECT	0 10 10		
NO OF FREQUENCIES	8		
NO OF TARGETS	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%
CLASS. FEATURES	A	A	A

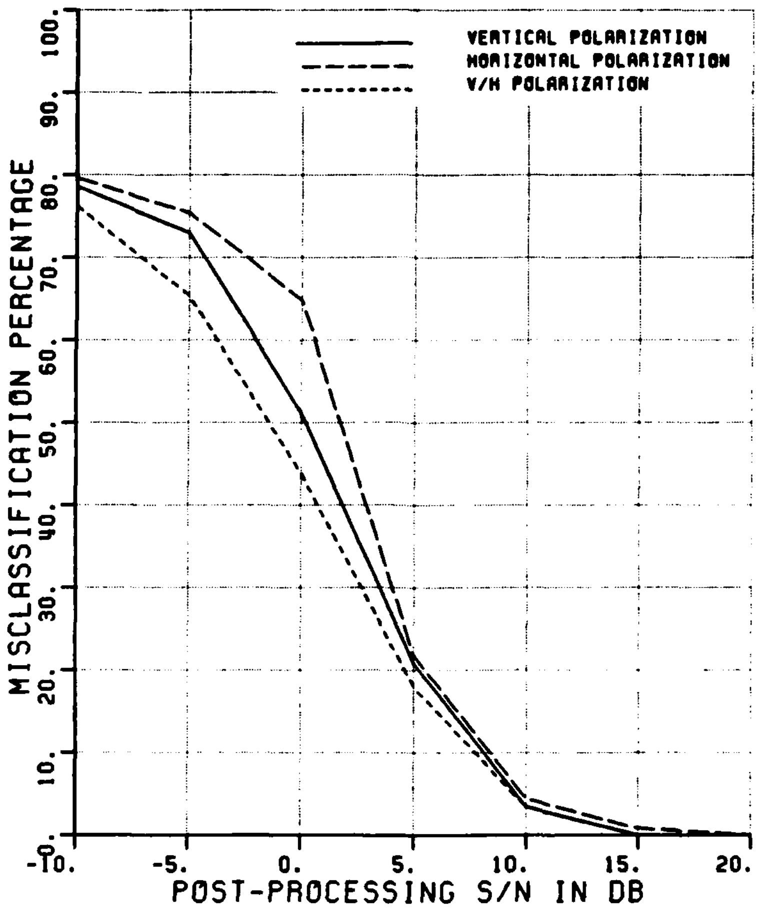

Figure A.46 Misclassification percentage versus post-processing SNR, comparing the performance of various polarizations.

CLASSIFICATION OF GND VCLS			
POLARIZATION	V	H	V/H
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN		
MIN,MAX,INC ASPECT	40	50	5
NO OF FREQUENCIES	8		
NO OF TARGETS	15	15	15
90% CI (@30%) +/-	2.8%	2.8%	2.8%
CLASS. FEATURES	A	A	A

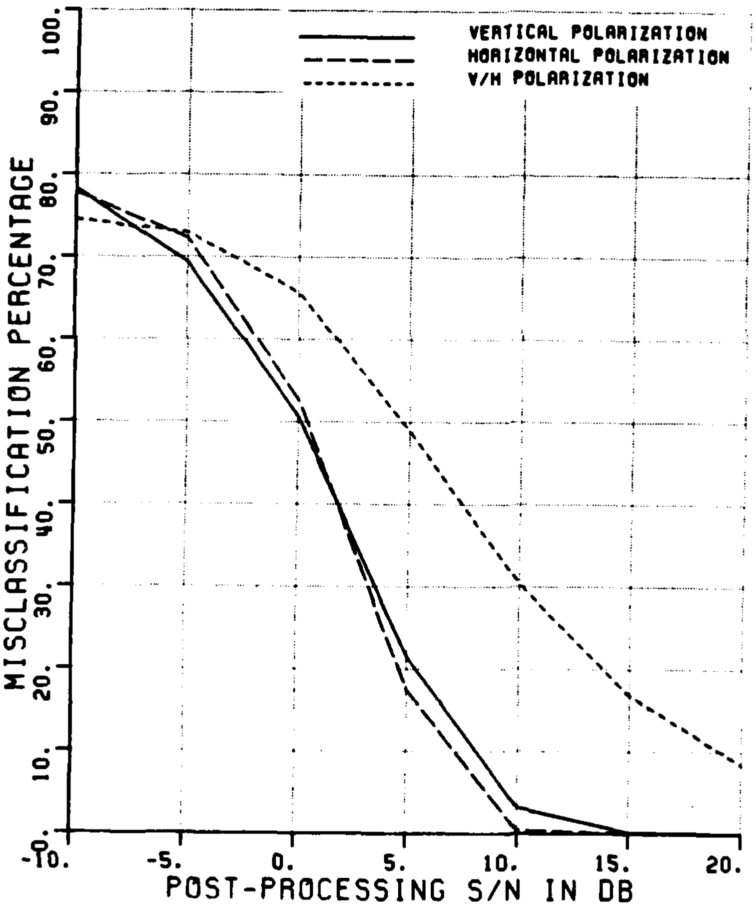

Figure A.47 Misclassification percentage versus post-processing SNR, comparing the performance of various polarizations.

CLASSIFICATION OF GND VCLS			
POLARIZATION	V	H	V/H
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN		
MIN,MAX,INC ASPECT	80	90	10
NO OF FREQUENCIES	8		
NO OF TARGETS	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%
CLASS. FEATURES	A	A	A

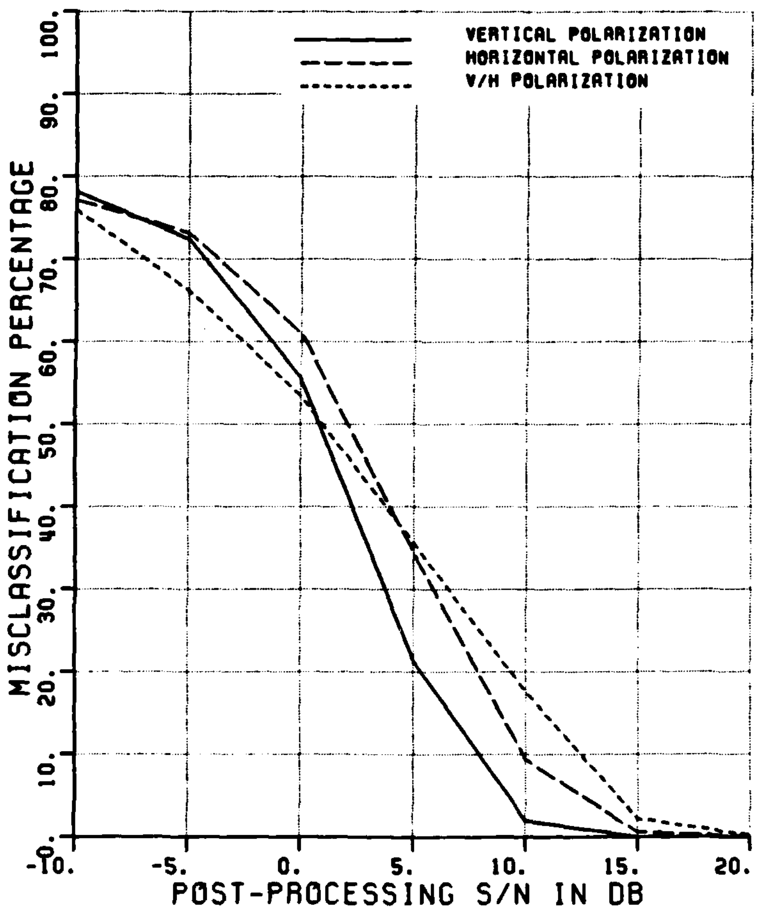

Figure A.48 Misclassification percentage versus post-processing SNR, comparing the performance of various polarizations.

CLASSIFICATION OF GND VCLS

POLARIZATION	V	H	V/H
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN		
MIN,MAX,INC ASPECT	0 10 10		
NO OF FREQUENCIES	8		
NO OF TARGETS	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%
CLASS. FEATURES	A&W	A&W	A&W

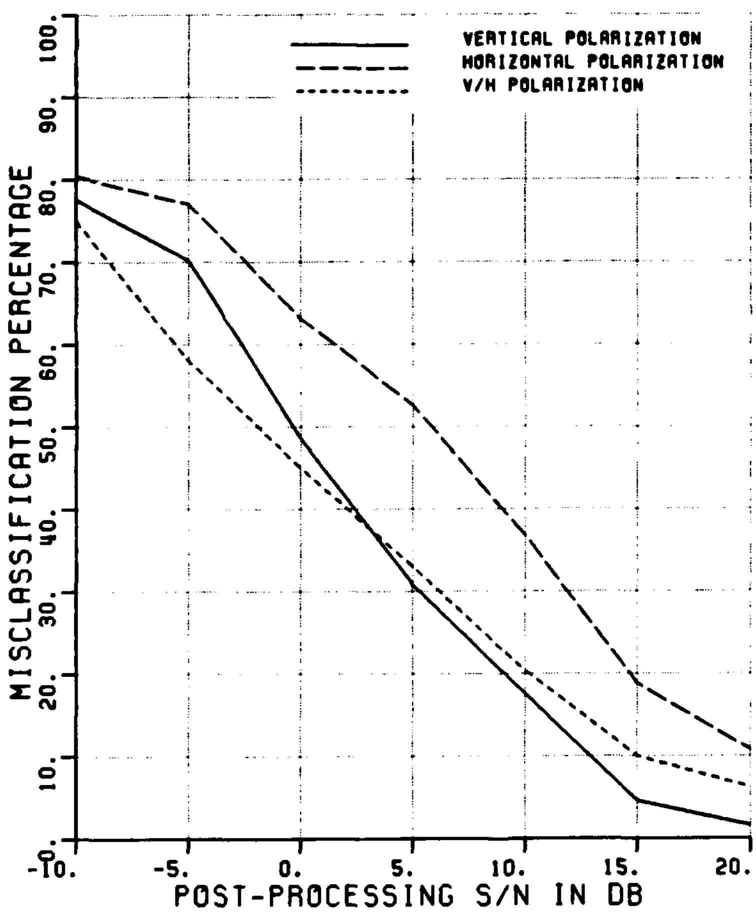

Figure A.49 Misclassification percentage versus post-processing SNR, comparing the performance of various polarizations.

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CLASSIFICATION OF GND VCLS
POLARIZATION          V     H     V/H
ELEV ASSUMED          KNOWN
ELEVATION (DEG.)      27
ASPECT ASSUMED        KNOWN
MIN,MAX,INC ASPECT    40  50   5
NO OF FREQUENCIES     8
NO OF TARGETS         15         15         15
90% CI (@30%) +/-     2.8%       2.8%       2.8%
CLASS. FEATURES       A&W        A&W        A&W
```

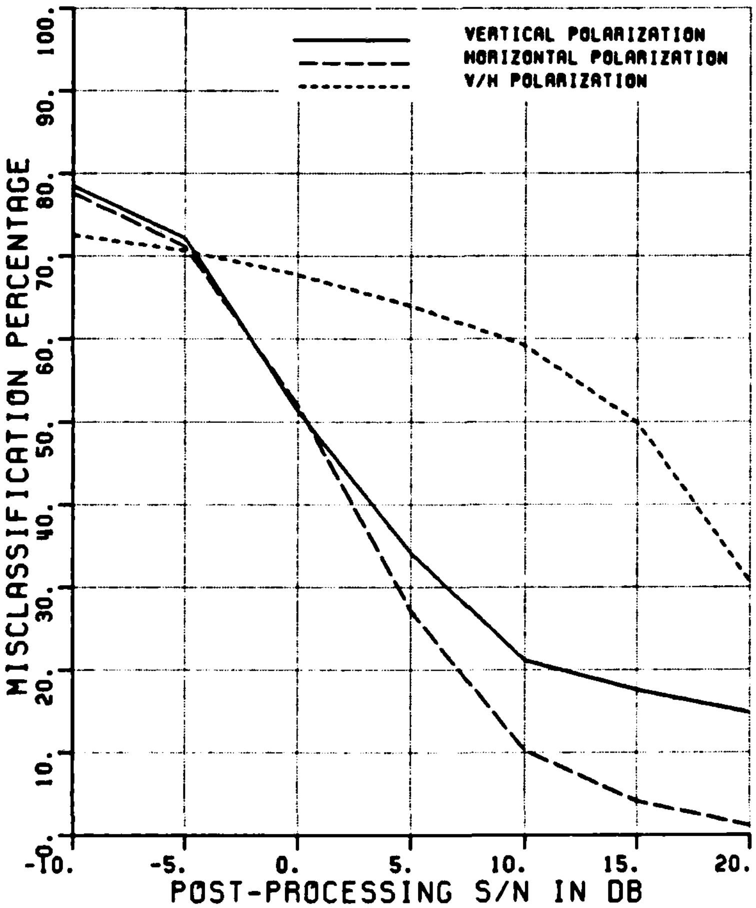


Figure A.50 Misclassification percentage versus post-processing SNR, comparing the performance of various polarizations.

CLASSIFICATION OF GND VCLS			
POLARIZATION	V	H	V/H
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN		
MIN,MAX,INC ASPECT	80 90 10		
NO OF FREQUENCIES	8		
NO OF TARGETS	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%
CLASS. FEATURES	A&W	A&W	A&W

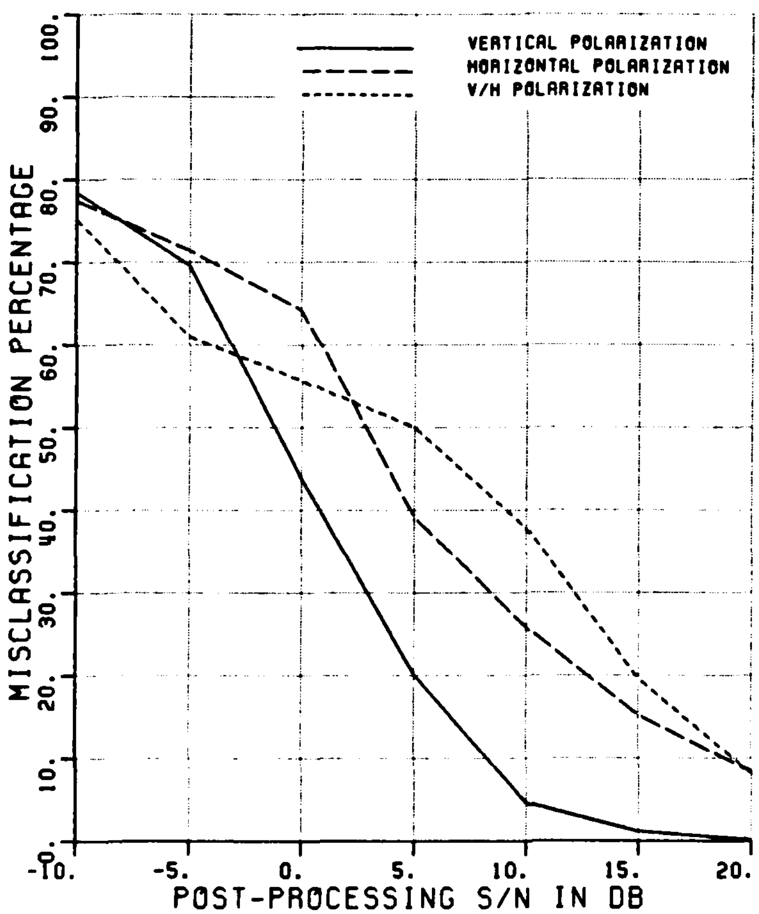


Figure A.51 Misclassification percentage versus post-processing SNR, comparing the performance of various polarizations.

CLASSIFICATION OF GND VCLS			
POLARIZATION	V	H	V/H
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN		
MIN,MAX,INC ASPECT	0 10 10		
NO OF FREQUENCIES	8		
NO OF TARGETS	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%
CLASS. FEATURES	W	W	W

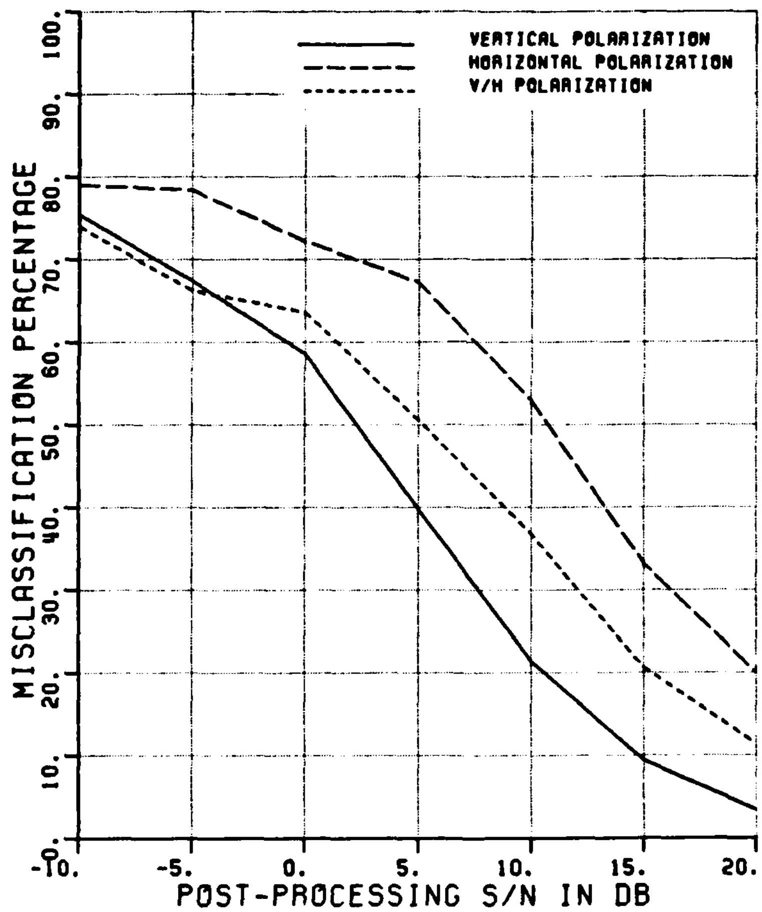


Figure A.52 Misclassification percentage versus post-processing SNR, comparing the performance of various polarizations.

CLASSIFICATION OF GND VCLS			
POLARIZATION	V	H	V/H
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN		
MIN,MAX,INC ASPECT	40	50	5
NO OF FREQUENCIES	8		
NO OF TARGETS	15	15	15
90% CI (@30%) +/-	2.8%	2.8%	2.8%
CLASS. FEATURES	W	W	W

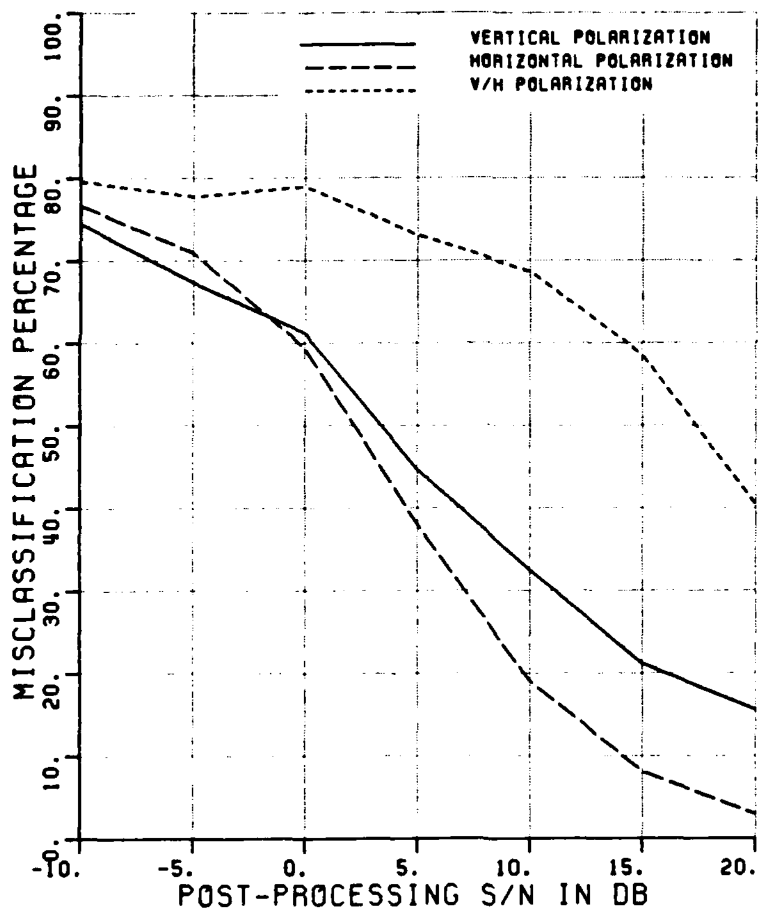


Figure A.53 Misclassification percentage versus post-processing SNR, comparing the performance of various polarizations.

CLASSIFICATION OF GND VCLS			
POLARIZATION	V	H	V/H
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN		
MIN,MAX,INC ASPECT	80 90 10		
NO OF FREQUENCIES	8		
NO OF TARGETS	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%
CLASS. FEATURES	W	W	W

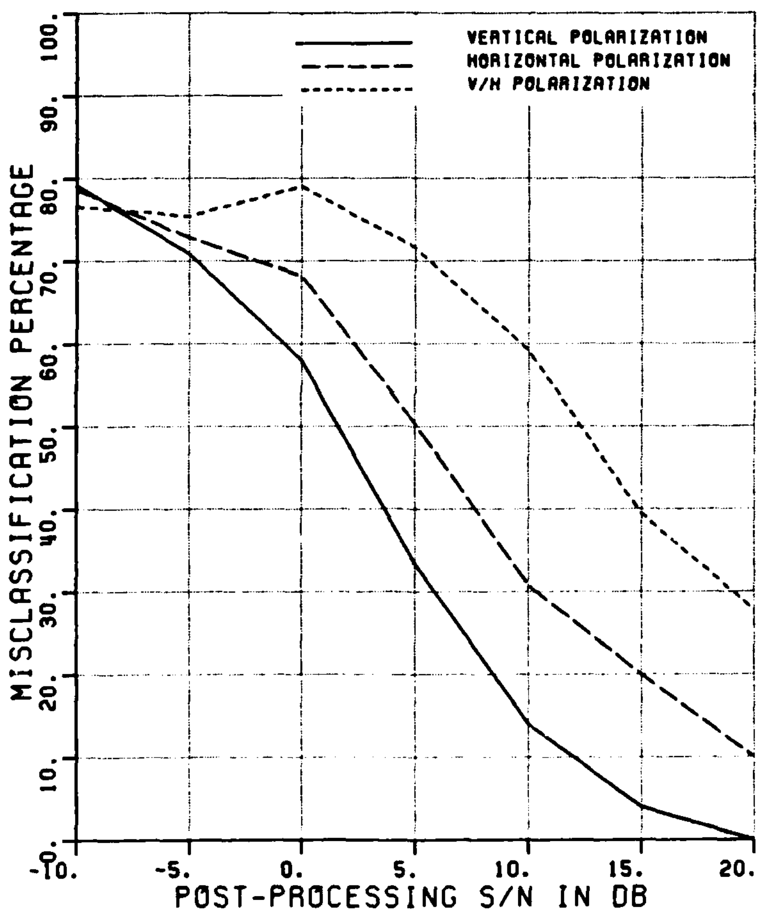


Figure A.54 Misclassification percentage versus post-processing SNR, comparing the performance of various polarizations.

CLASSIFICATION OF GND VCLS			
POLARIZATION	V	H	V/H
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN		
MIN,MAX,INC ASPECT	0 10 10		
NO OF FREQUENCIES	8		
NO OF TARGETS	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%
CLASS. FEATURES	T	T	T

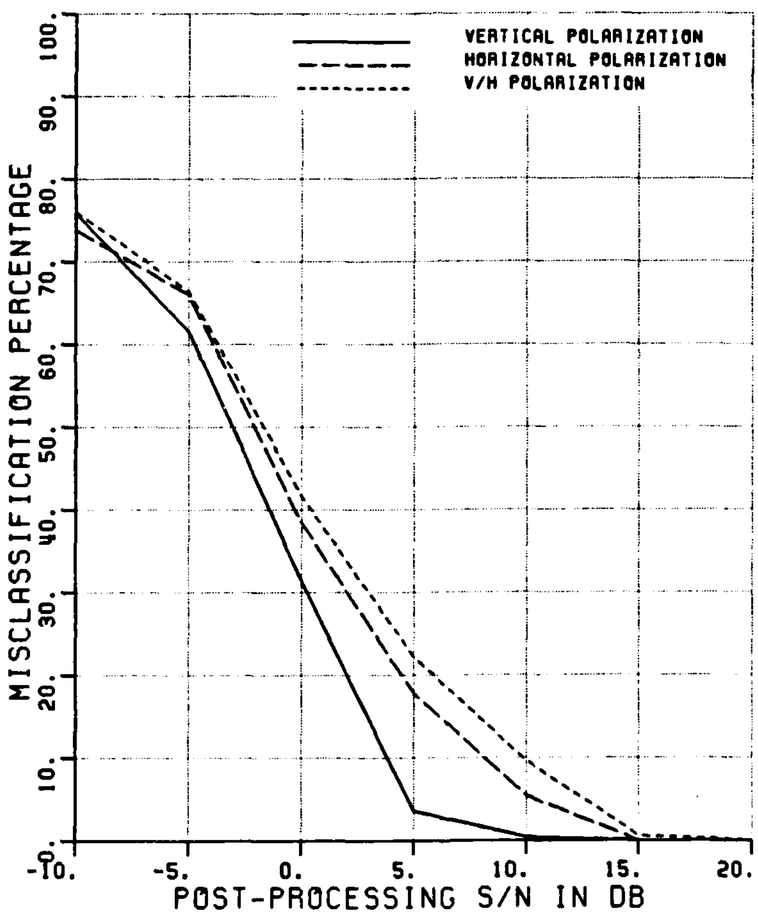


Figure A.55 Misclassification percentage versus post-processing SNR, comparing the performance of various polarizations.

CLASSIFICATION OF GND VCLS

POLARIZATION	V	H	V/H
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN		
MIN,MAX,INC ASPECT	40	50	5
NO OF FREQUENCIES	8		
NO OF TARGETS	15	15	15
90% CI (●30%) +/-	2.8%	2.8%	2.8%
CLASS. FEATURES	T	T	T

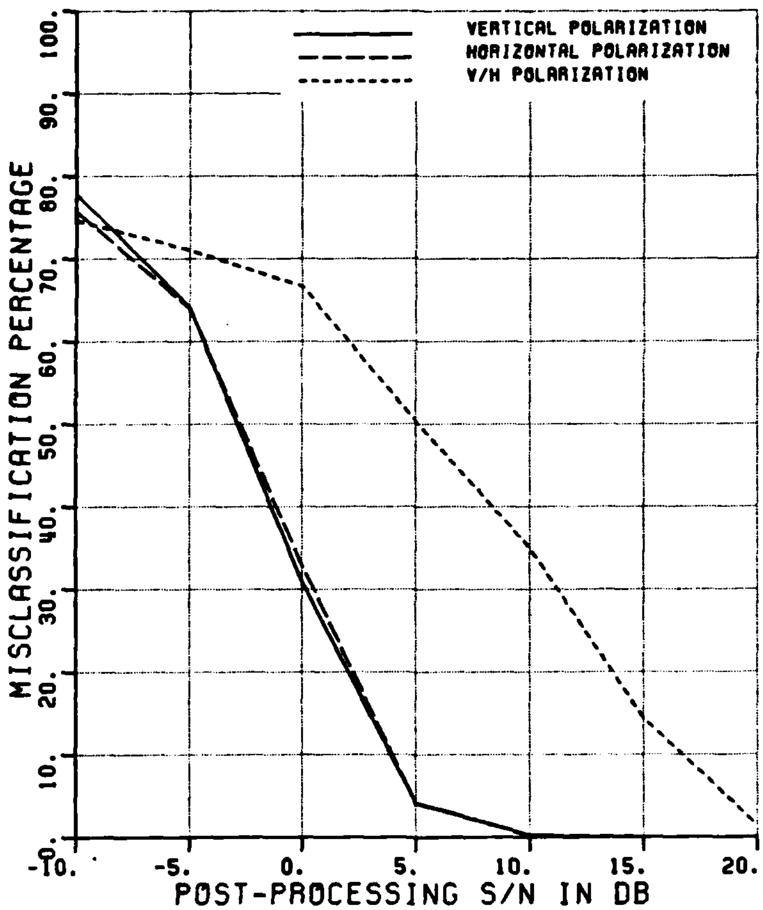


Figure A.56 Misclassification percentage versus post-processing SNR, comparing the performance of various polarizations.

CLASSIFICATION OF GND VCLS			
POLARIZATION	V	H	V/H
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN		
MIN,MAX,INC ASPECT	80 90 10		
NO OF FREQUENCIES	8		
NO OF TARGETS	10	10	10
90% CI (@30%) +/-	3.4%	3.4%	3.4%
CLASS. FEATURES	T	T	T

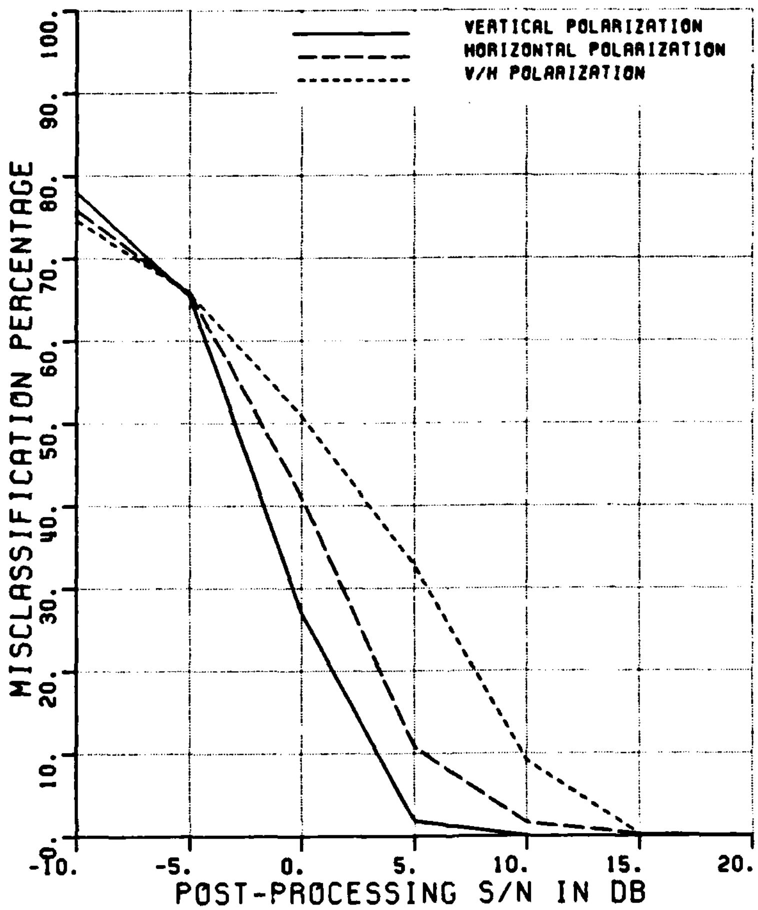


Figure A.57 Misclassification percentage versus post-processing SNR, comparing the performance of various polarizations.

CLASSIFICATION OF GND VCLS
POLARIZATION V
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN / KNOWN
MIN,MAX,INC ASPECT 0 10 10, 40 50 5, 80 90 10
NO OF FREQUENCIES 8
NO OF TARGETS 10 15 10
90% CI (@30%) +/- 3.4% 2.8% 3.4%
CLASS. FEATURES A A A

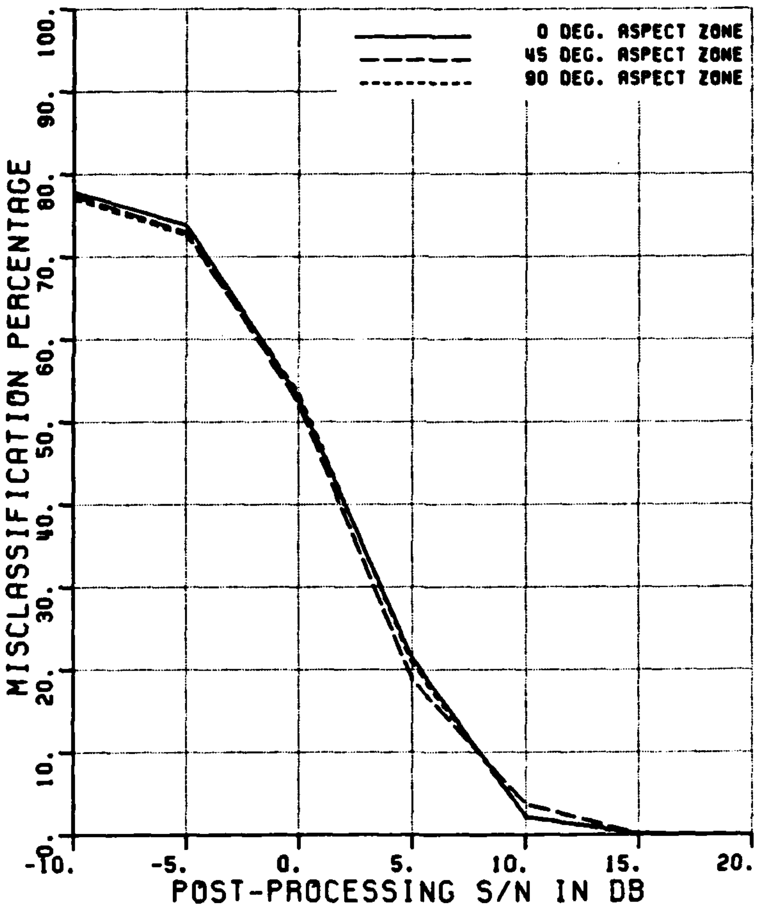


Figure A.58 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones.

CLASSIFICATION OF GND VCLS
POLARIZATION H
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN / KNOWN
MIN,MAX,INC ASPECT 0 10 10, 40 50 5, 80 90 10
NO OF FREQUENCIES 8
NO OF TARGETS 10 15 10
90% CI (@30%) +/- 3.4% 2.8% 3.4%
CLASS. FEATURES A A A

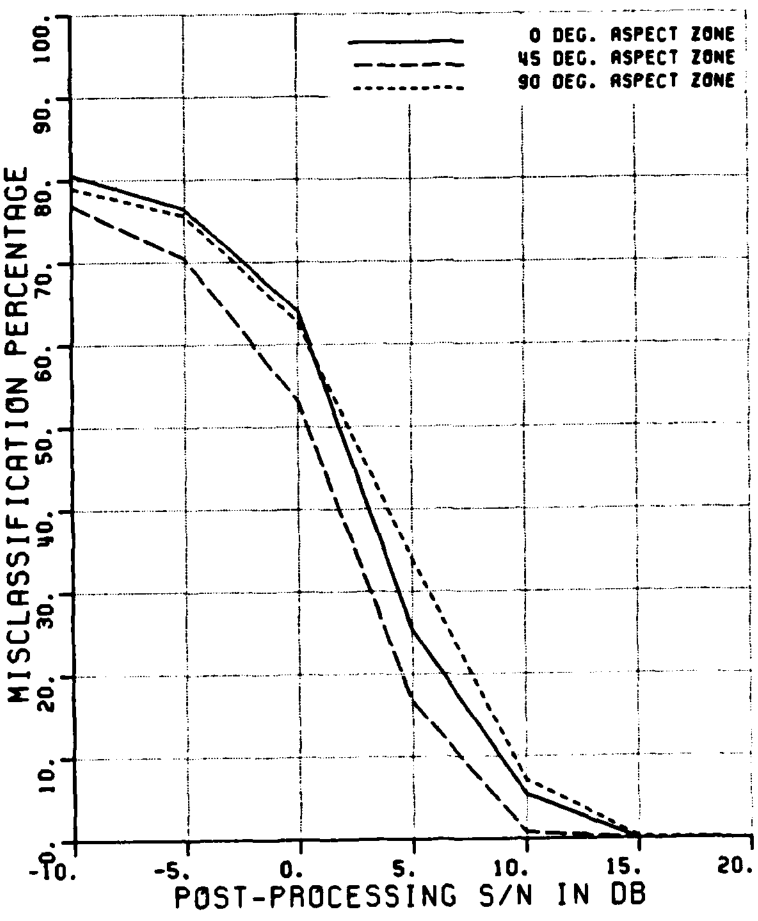


Figure A.59 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones.

CLASSIFICATION OF GND VCLS			
POLARIZATION	V/H		
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN	/	KNOWN
MIN,MAX,INC ASPECT	0 10 10,	40 50 5,	80 90 10
NO OF FREQUENCIES	8		
NO OF TARGETS	10	15	10
90% CI (@30%) +/-	3.4%	2.8%	3.4%
CLASS. FEATURES	A	A	A

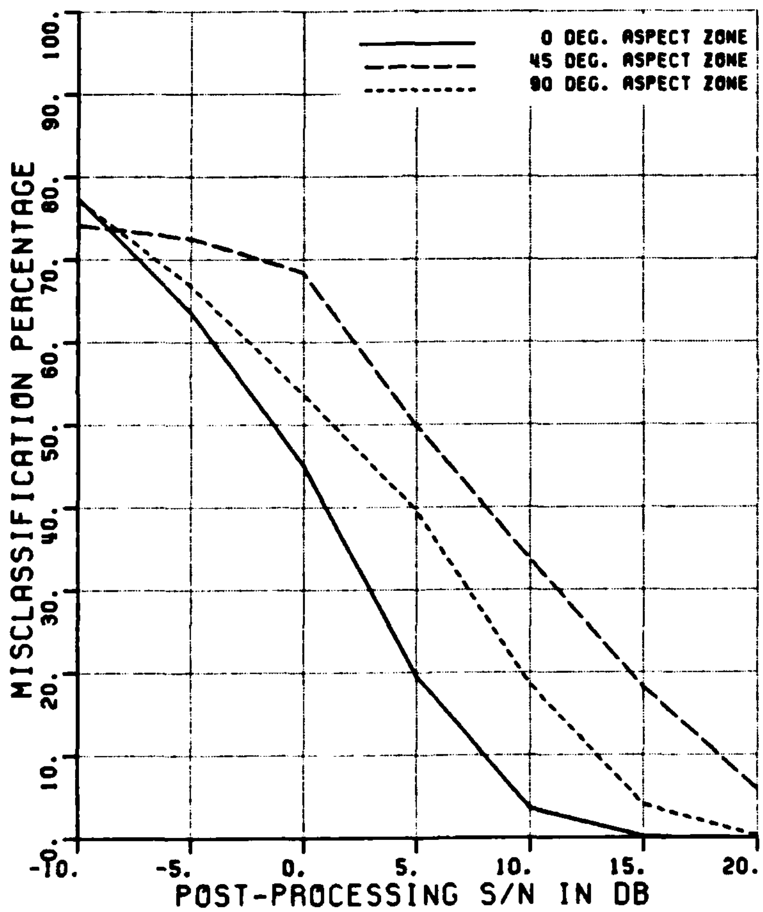


Figure A.60 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones.

CLASSIFICATION OF GND VCLS			
POLARIZATION	V		
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN	/	KNOWN
MIN,MAX,INC ASPECT	0 10 10,	40 50 5,	80 90 10
NO OF FREQUENCIES	8		
NO OF TARGETS	10	15	10
90% CI (@30%) +/-	3.4%	2.8%	3.4%
CLASS. FEATURES	A&W	A&W	A&W

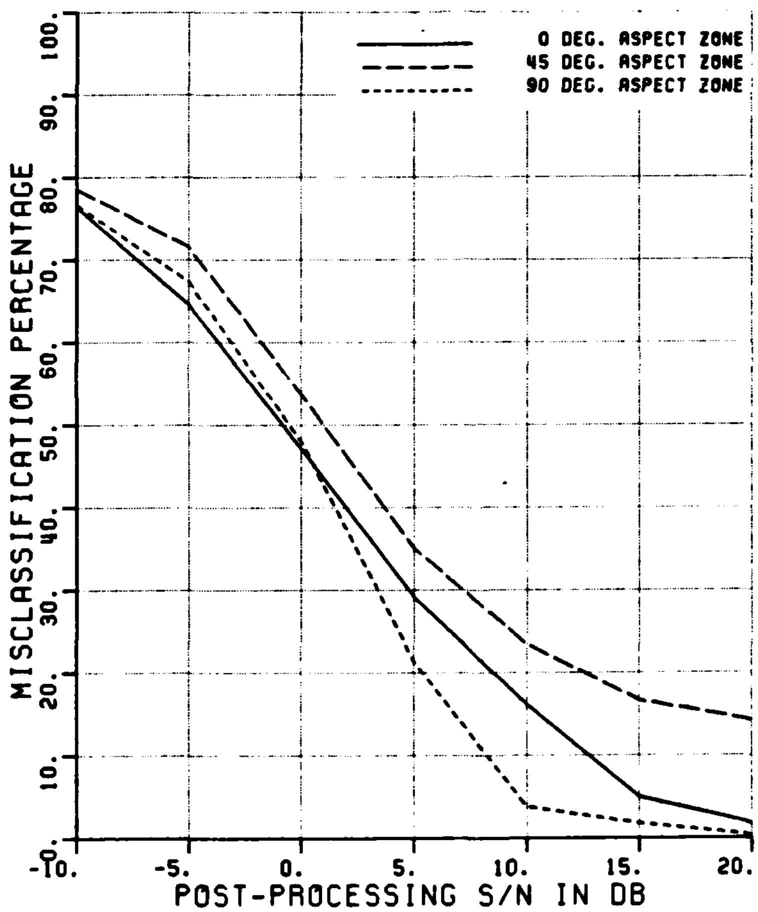


Figure A.61 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones.

CLASSIFICATION OF GND VCLS			
POLARIZATION	H		
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN	/	KNOWN
MIN,MAX,INC ASPECT	0 10 10,	40 50 5,	80 90 10
NO OF FREQUENCIES	8		
NO OF TARGETS	10	15	10
90% CI (@30%) +/-	3.4%	2.8%	3.4%
CLASS. FEATURES	A&W	A&W	A&W

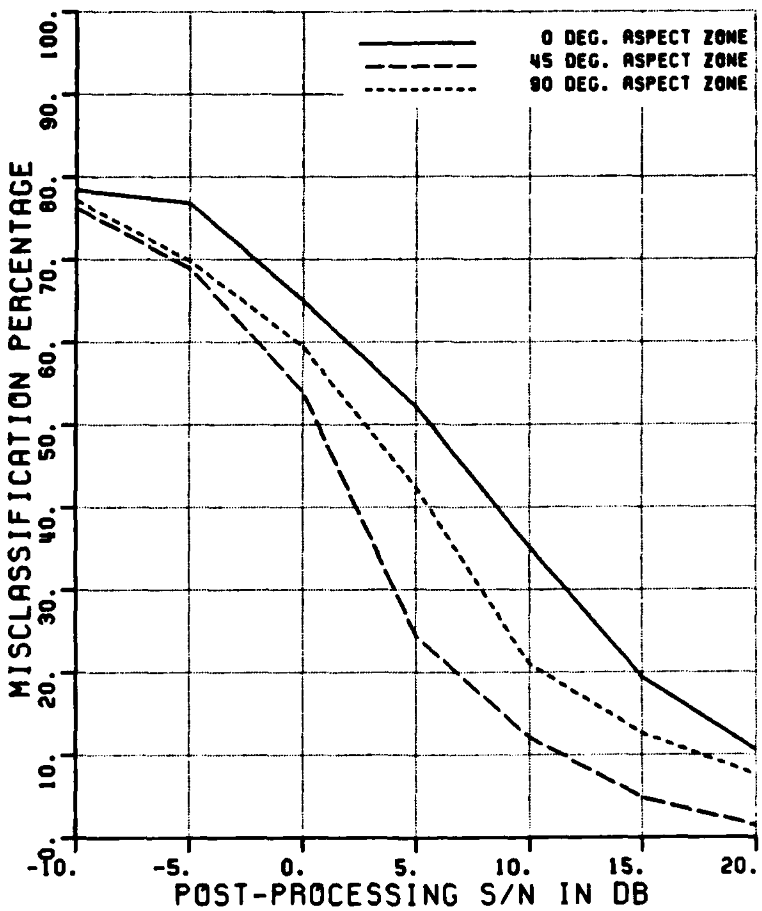


Figure A.62 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones.

CLASSIFICATION OF GND VCLS	
POLARIZATION	V/H
ELEV ASSUMED	KNOWN
ELEVATION (DEG.)	27
ASPECT ASSUMED	KNOWN / KNOWN
MIN,MAX,INC ASPECT	0 10 10, 40 50 5, 80 90 10
NO OF FREQUENCIES	8
NO OF TARGETS	10 15 10
90% CI (@30%) +/-	3.4% 2.8% 3.4%
CLASS. FEATURES	A&W A&W A&W

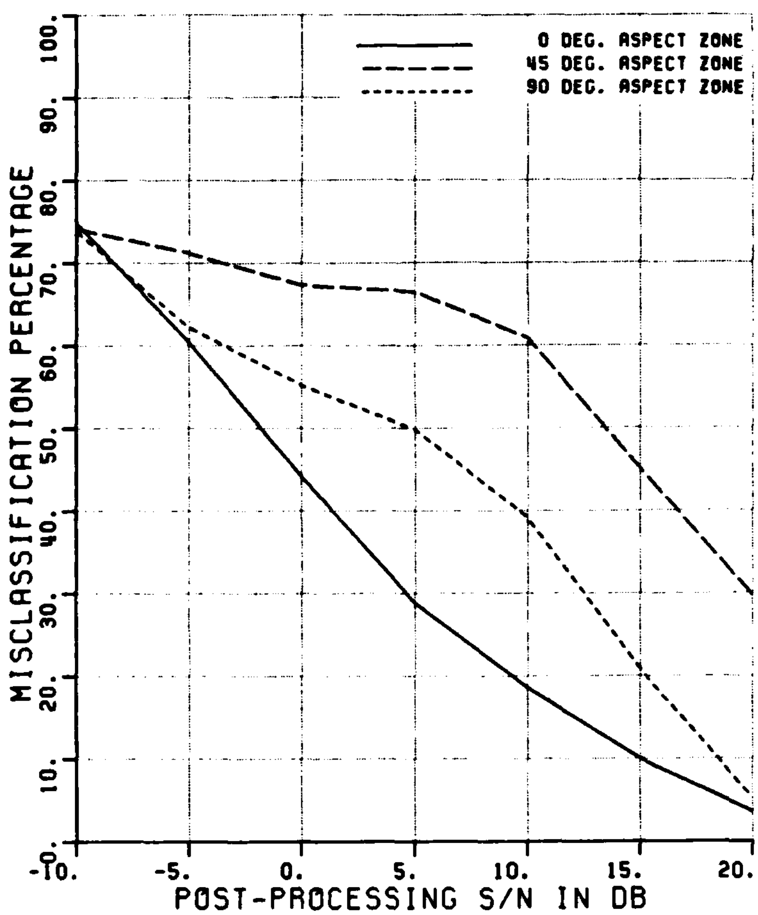


Figure A.63 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones.

CLASSIFICATION OF GND VCLS
POLARIZATION V
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN / KNOWN
MIN,MAX,INC ASPECT 0 10 10, 40 50 5, 80 90 10
NO OF FREQUENCIES 8
NO OF TARGETS 10 15 10
90% CI (@30%) +/- 3.4% 2.8% 3.4%
CLASS. FEATURES W W W

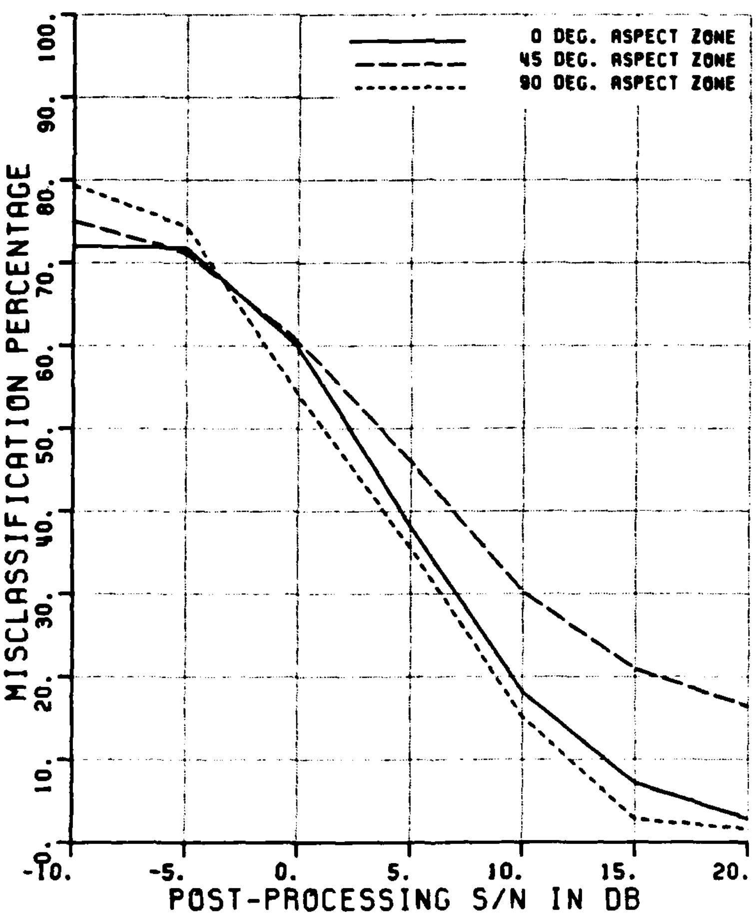


Figure A.64 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones.

```
CLASSIFICATION OF GND VCLS
POLARIZATION        H
ELEV ASSUMED        KNOWN
ELEVATION (DEG.)    27
ASPECT ASSUMED      KNOWN       /  KNOWN
MIN,MAX,INC ASPECT   0  10  10,  40  50   5,  80  90  10
NO OF FREQUENCIES   8
NO OF TARGETS       10        15        10
90% CI (@30%) +/-   3.4%     2.8%     3.4%
CLASS. FEATURES     W    W    W
```

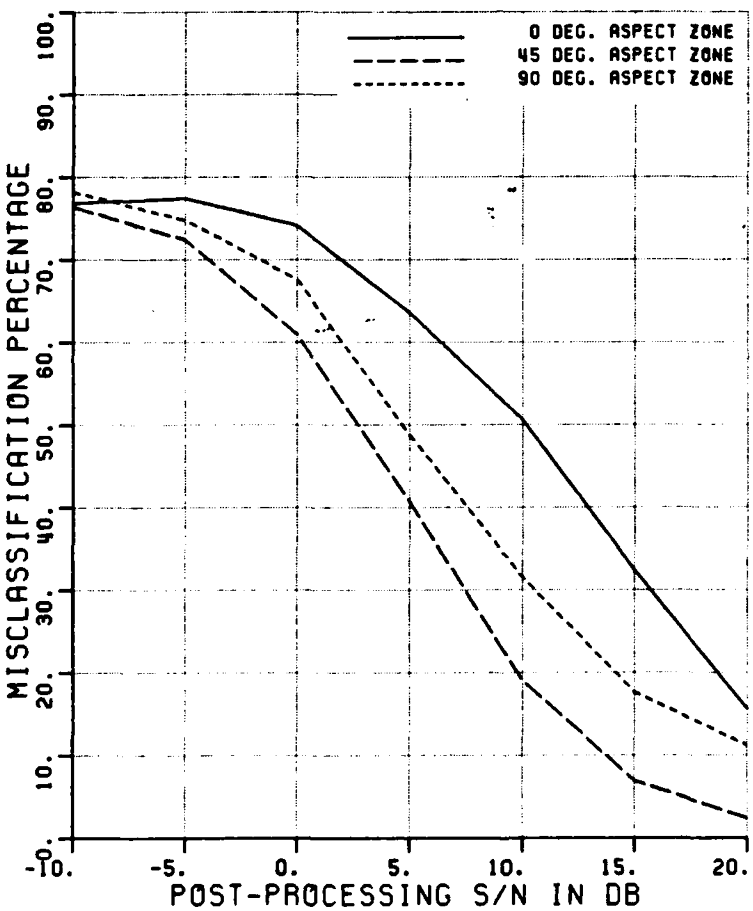


Figure A.65 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones.

CLASSIFICATION OF GND VCLS

POLARIZATION	V/H		
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN	/	KNOWN
MIN,MAX,INC ASPECT	0 10 10,	40 50 5,	80 90 10
NO OF FREQUENCIES	8		
NO OF TARGETS	10	15	10
90% CI (@30%) +/-	3.4%	2.8%	3.4%
CLASS. FEATURES	W	W	W

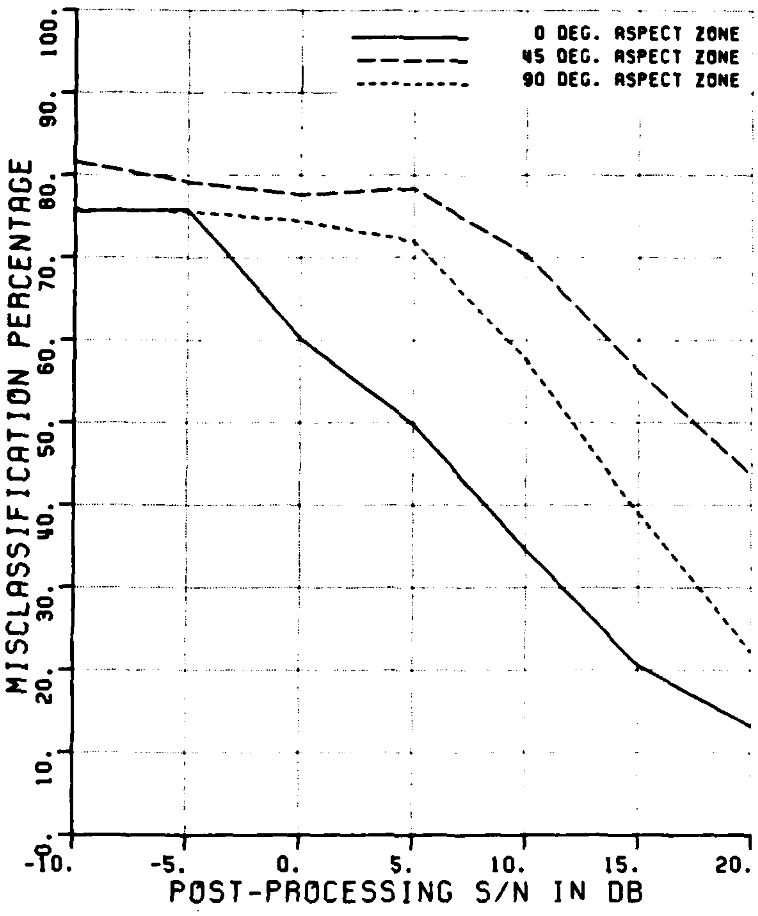


Figure A.66 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones.

CLASSIFICATION OF GND VCLS
POLARIZATION V
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN / KNOWN
MIN,MAX,INC ASPECT 0 10 10, 40 50 5, 80 90 10
NO OF FREQUENCIES 8
NO OF TARGETS 10 15 10
90% CI (@30%) +/- 3.4% 2.8% 3.4%
CLASS. FEATURES T T T

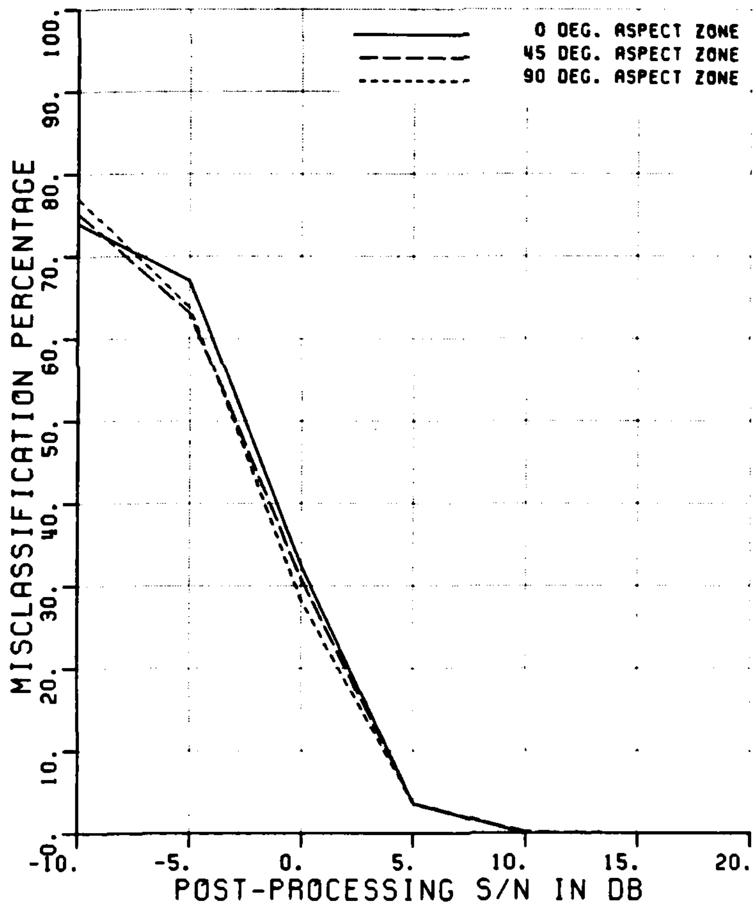


Figure A.67 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones.

CLASSIFICATION OF GND VCLS
POLARIZATION H
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN / KNOWN
MIN,MAX,INC ASPECT 0 10 10, 40 50 5, 80 90 10
NO OF FREQUENCIES 8
NO OF TARGETS 10 15 10
90% CI (@30%) +/- 3.4% 2.8% 3.4%
CLASS. FEATURES T T T

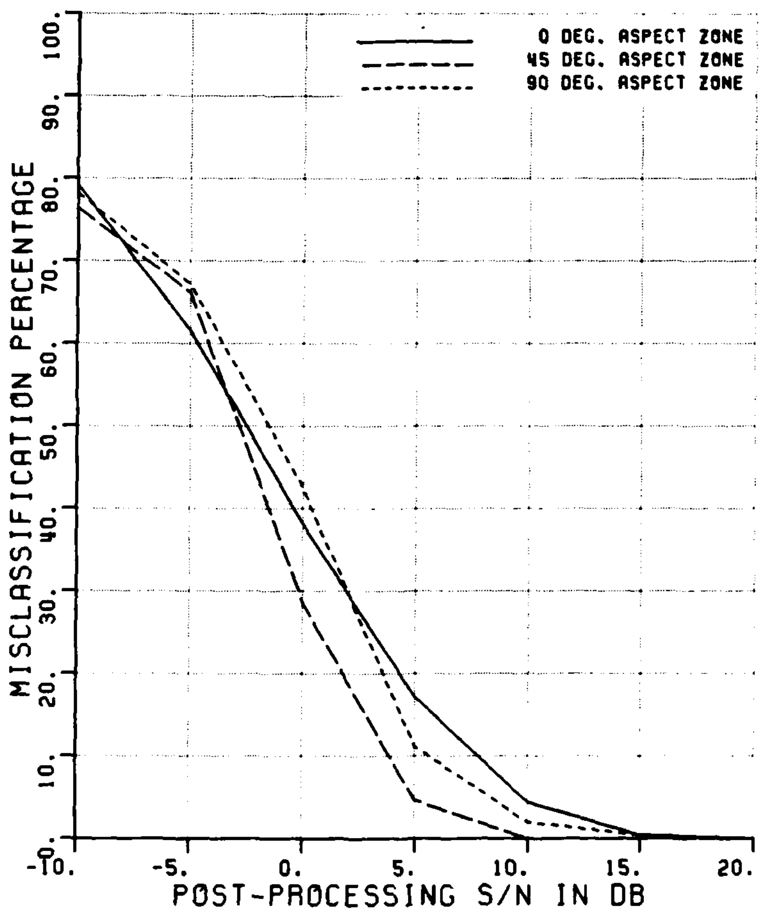


Figure A.68 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones.

CLASSIFICATION OF GND VCLS									
POLARIZATION	V/H								
ELEV ASSUMED	KNOWN								
ELEVATION (DEG.)	27								
ASPECT ASSUMED	KNOWN		/	KNOWN					
MIN,MAX,INC ASPECT	0	10	10,	40	50	5,	80	90	10
NO OF FREQUENCIES	8								
NO OF TARGETS	10	15	10						
90% CI (@30%) +/-	3.4%	2.8%	3.4%						
CLASS. FEATURES	T	T	T						

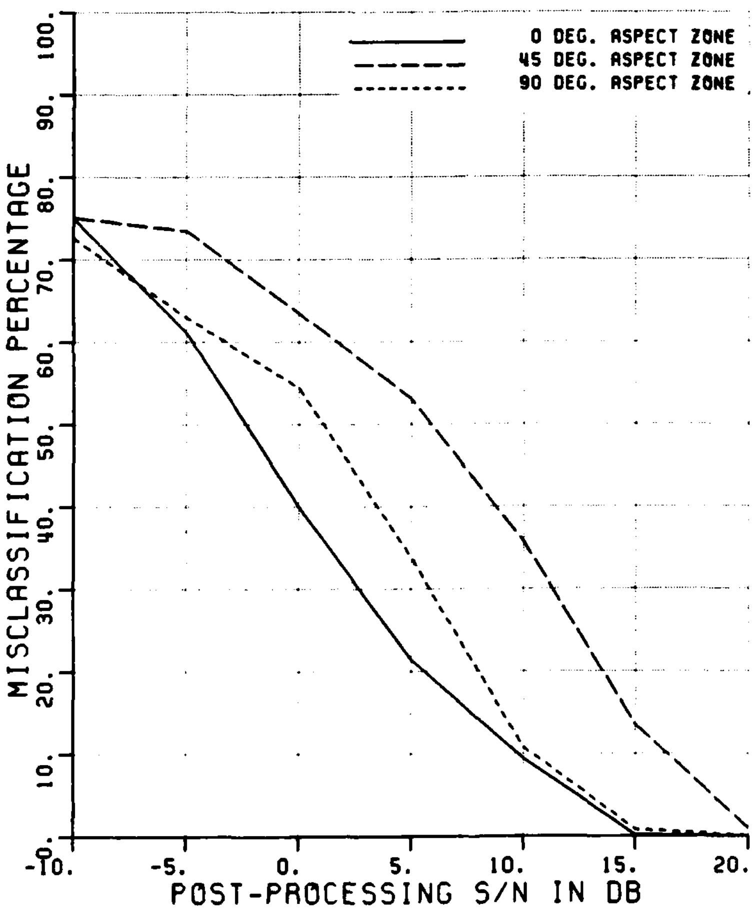


Figure A.69 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones.

CLASSIFICATION OF GND VCLS			
POLARIZATION	V		
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN	/ KNOWN	
MIN,MAX,INC ASPECT	0 10 10,	40 50 5,	80 90 10
NO OF FREQUENCIES	8		
NO OF TARGETS	10	15	10
90% CI (@30%) +/-	3.4%	2.8%	3.4%
CLASS. FEATURES	A	A	A
ASP ERR IN CURVE	1	2	3

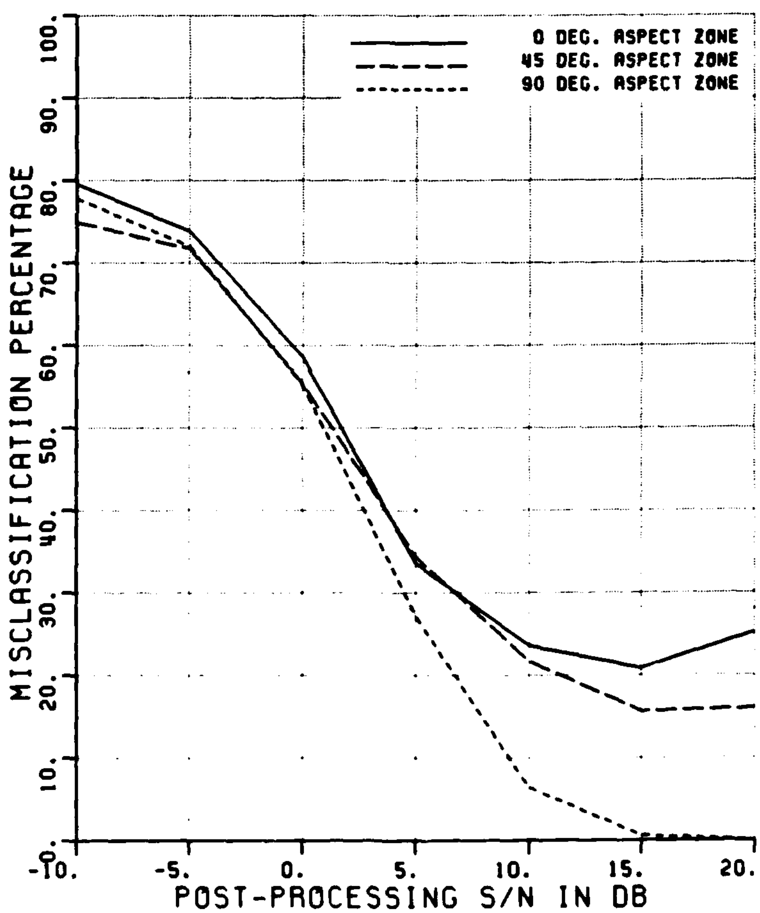


Figure A.70 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones, with a forced error in aspect angle.

CLASSIFICATION OF GND VCLS
POLARIZATION H
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN / KNOWN
MIN,MAX,INC ASPECT 0 10 10, 40 50 5, 80 90 10
NO OF FREQUENCIES 8
NO OF TARGETS 10 15 10
90% CI (@30%) +/- 3.4% 2.8% 3.4%
CLASS. FEATURES A A A
ASP ERR IN CURVE 1 2 3

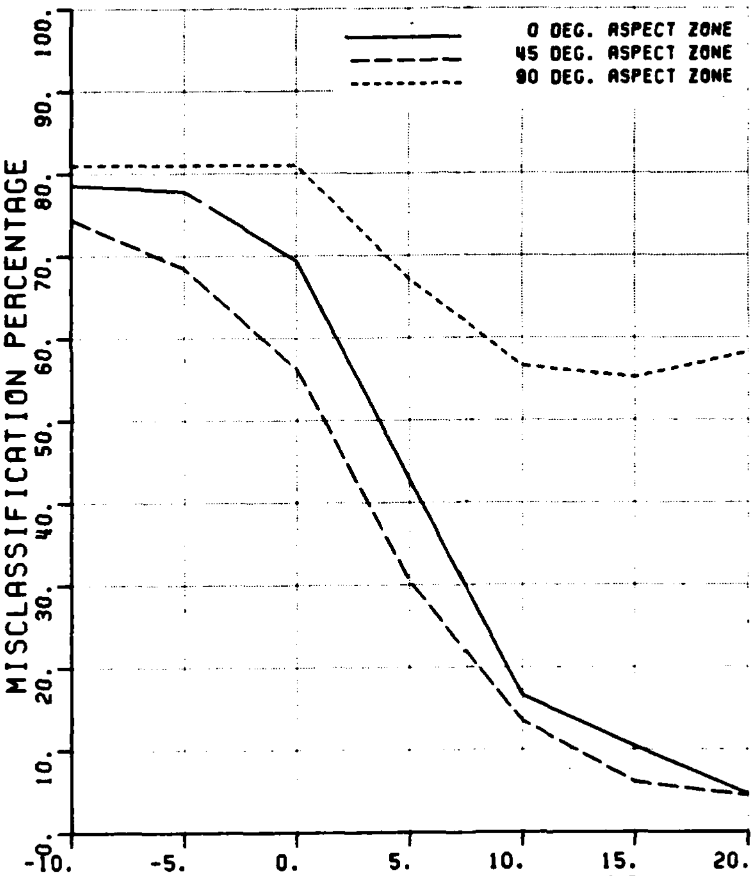


Figure A.71 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones, with a forced error in aspect angle.

```
CLASSIFICATION OF GND VCLS
POLARIZATION        V/H
ELEV ASSUMED        KNOWN
ELEVATION (DEG.)    27
ASPECT ASSUMED      KNOWN        /  KNOWN
MIN,MAX,INC ASPECT    0  10  10,  40  50   5,  80  90  10
NO OF FREQUENCIES   8
NO OF TARGETS       10        15        10
90% CI (@30%) +/-   3.4%     2.8%     3.4%
CLASS. FEATURES     A     A     A
ASP ERR IN CURVE    1        2        3
```

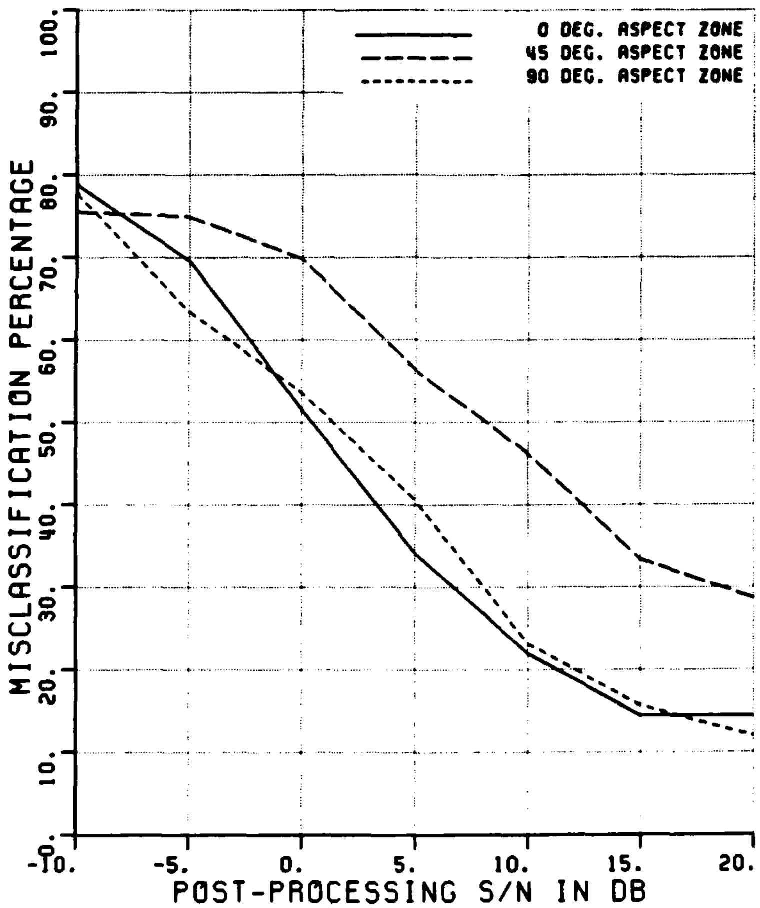


Figure A.72 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones, with a forced error in aspect angle.

CLASSIFICATION OF GND VCLS			
POLARIZATION	V		
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN	/	KNOWN
MIN,MAX,INC ASPECT	0 10 10,	40 50 5,	80 90 10
NO OF FREQUENCIES	8		
NO OF TARGETS	10	15	10
90% CI (@30%) +/-	3.4%	2.8%	3.4%
CLASS. FEATURES	A&W	A&W	A&W
ASP ERR IN CURVE	1	2	3

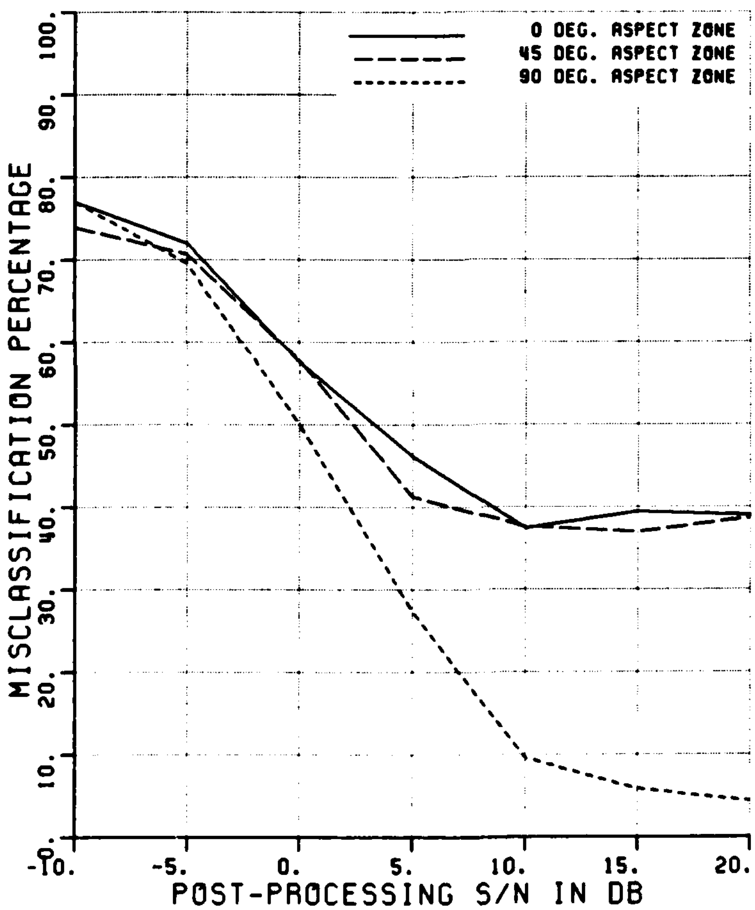


Figure A.73 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones, with a forced error in aspect angle.

CLASSIFICATION OF GND VCLS			
POLARIZATION	H		
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN	/ KNOWN	
MIN,MAX,INC ASPECT	0 10 10,	40 50 5,	80 90 10
NO OF FREQUENCIES	8		
NO OF TARGETS	10	15	10
90% CI (@30%) +/-	3.4%	2.8%	3.4%
CLASS. FEATURES	A&W	A&W	A&W
ASP ERR IN CURVE	1	2	3

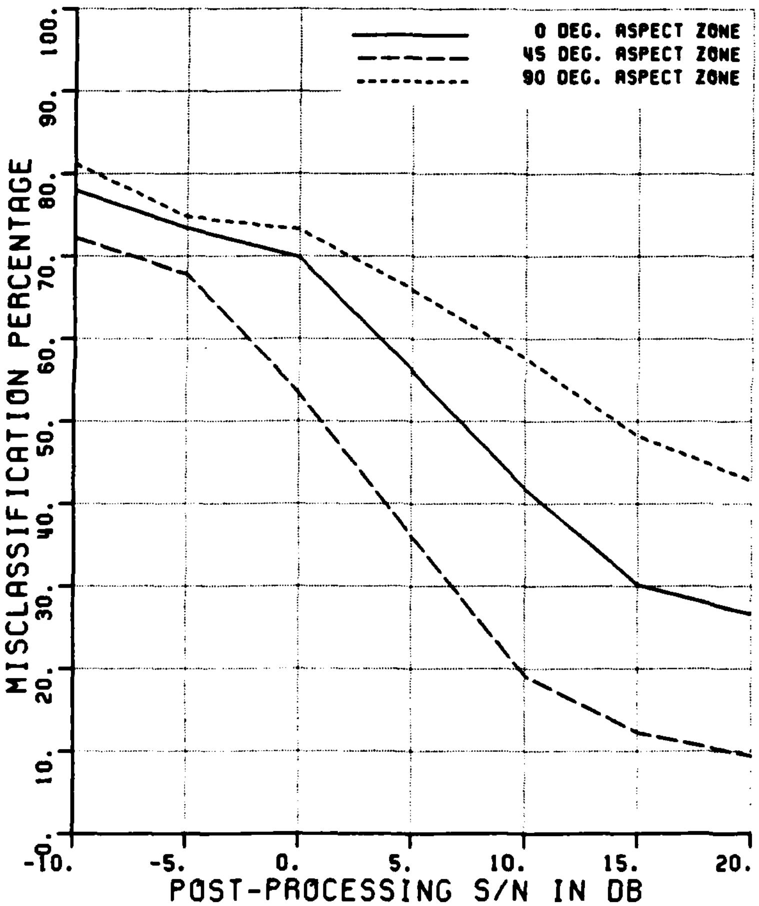


Figure A.74 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones, with a forced error in aspect angle.

CLASSIFICATION OF GND VCLS	
POLARIZATION	V/H
ELEV ASSUMED	KNOWN
ELEVATION (DEG.)	27
ASPECT ASSUMED	KNOWN / KNOWN
MIN,MAX,INC ASPECT	0 10 10, 40 50 5, 80 90 10
NO OF FREQUENCIES	8
NO OF TARGETS	10 15 10
90% CI (@30%) +/-	3.4% 2.8% 3.4%
CLASS. FEATURES	A&W A&W A&W
ASP ERR IN CURVE	1 2 3

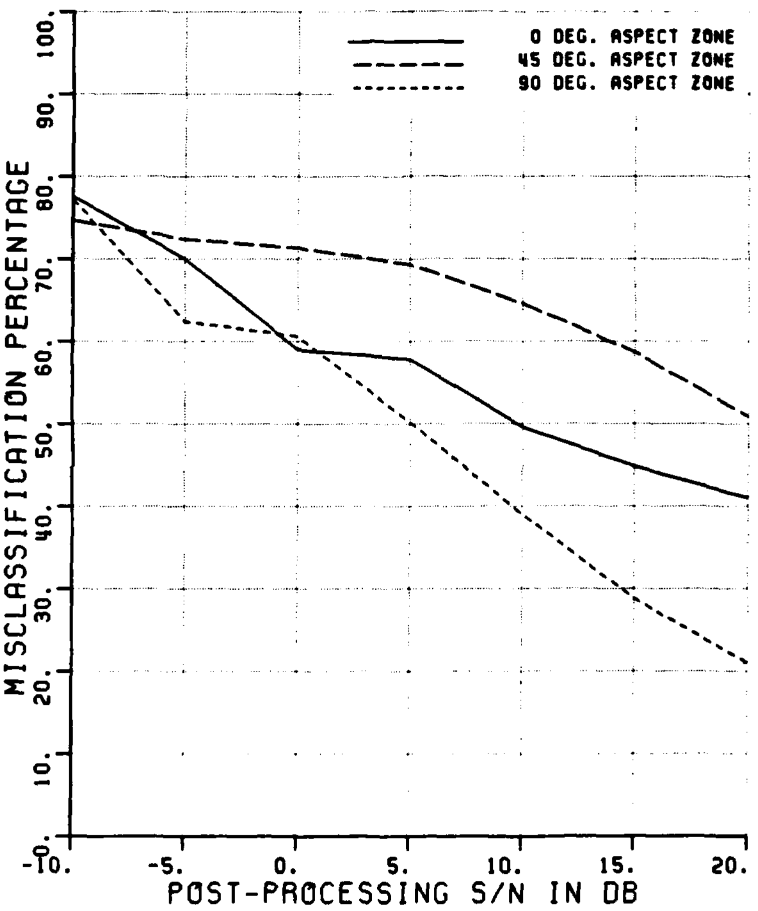


Figure A.75 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones, with a forced error in aspect angle.

CLASSIFICATION OF GND VCLS
POLARIZATION V
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN / KNOWN
MIN,MAX,INC ASPECT 0 10 10, 40 50 5, 80 90 10
NO OF FREQUENCIES 8
NO OF TARGETS 10 15 10
90% CI (@30%) +/- 3.4% 2.8% 3.4%
CLASS. FEATURES W W W
ASP ERR IN CURVE 1 2 3

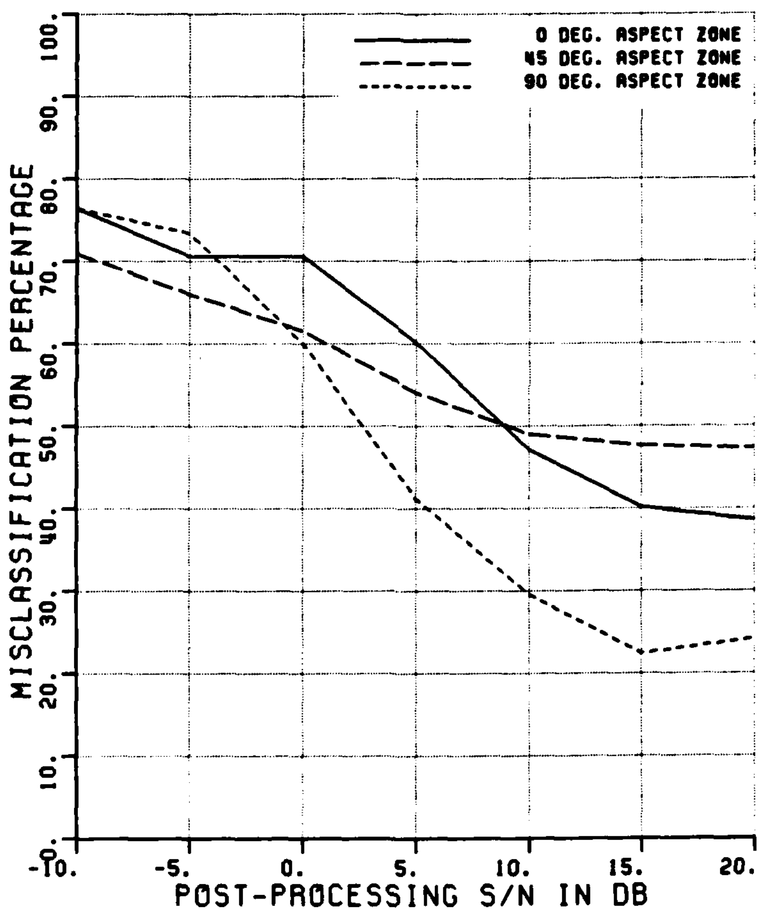


Figure A.76 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones, with a forced error in aspect angle.

CLASSIFICATION OF GND VCLS	
POLARIZATION	H
ELEV ASSUMED	KNOWN
ELEVATION (DEG.)	27
ASPECT ASSUMED	KNOWN / KNOWN
MIN,MAX,INC ASPECT	0 10 10, 40 50 5, 80 90 10
NO OF FREQUENCIES	8
NO OF TARGETS	10 15 10
90% CI (@30%) +/-	3.4% 2.8% 3.4%
CLASS. FEATURES	W W W
ASP ERR IN CURVE	**1 2 3**

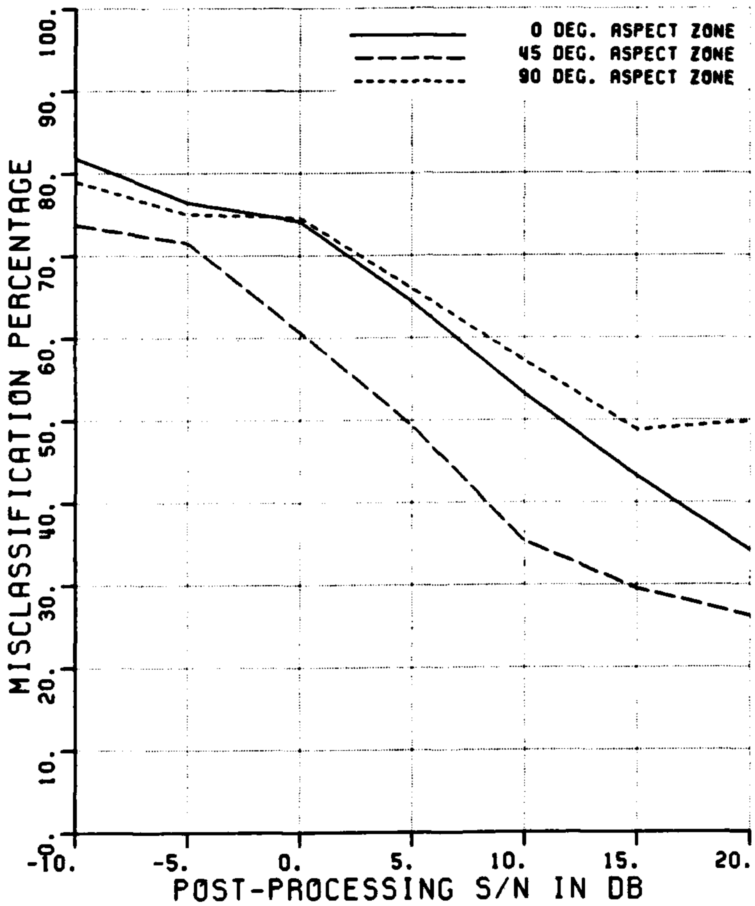


Figure A.77 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones, with a forced error in aspect angle.

CLASSIFICATION OF GND VCLS
POLARIZATION V/H
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN / KNOWN
MIN,MAX,INC ASPECT 0 10 10, 40 50 5, 80 90 10
NO OF FREQUENCIES 8
NO OF TARGETS 10 15 10
90% CI (@30%) +/- 3.4% 2.8% 3.4%
CLASS. FEATURES W W W
ASP ERR IN CURVE 1 2 3

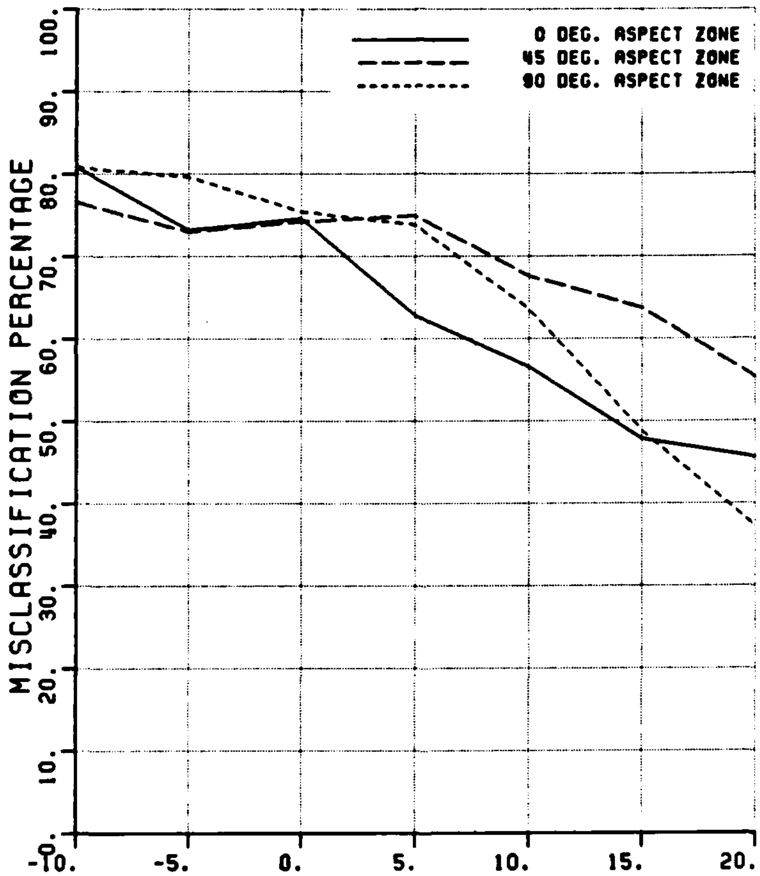


Figure A.78 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones, with a forced error in aspect angle.

CLASSIFICATION OF GND VCLS
POLARIZATION V
ELEV ASSUMED KNOWN
ELEVATION (DEG.) 27
ASPECT ASSUMED KNOWN / KNOWN
MIN,MAX,INC ASPECT 0 10 10, 40 50 5, 80 90 10
NO OF FREQUENCIES 8
NO OF TARGETS 10 15 10
90% CI (@30%) +/- 3.4% 2.8% 3.4%
CLASS. FEATURES T T T
ASP ERR IN CURVE 1 2 3

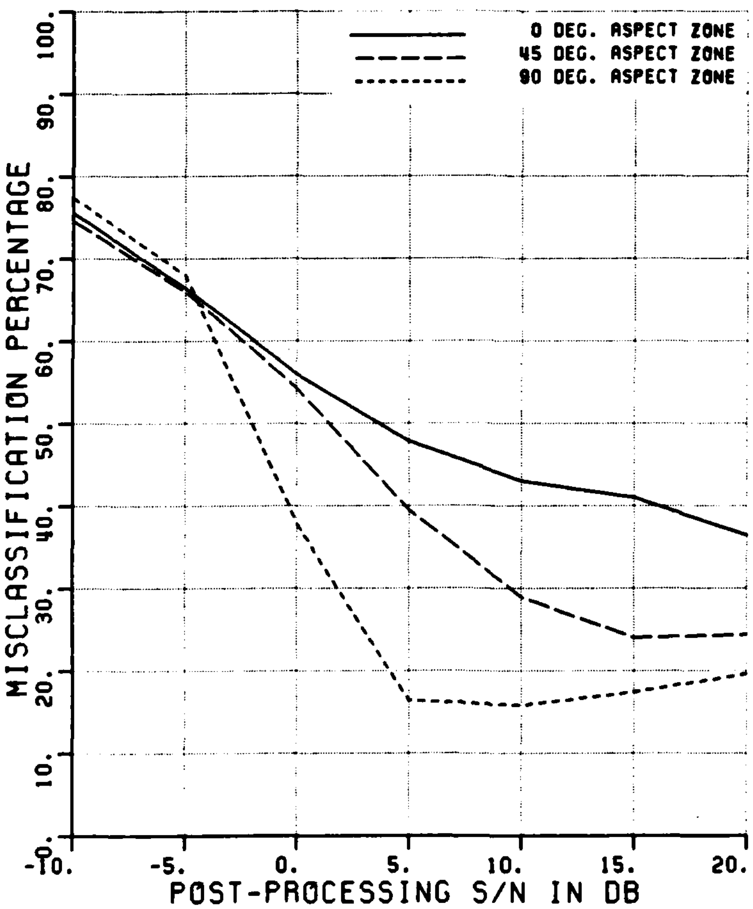


Figure A.79 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones, with a forced error in aspect angle.

CLASSIFICATION OF GND VCLS				
POLARIZATION	H			
ELEV ASSUMED	KNOWN			
ELEVATION (DEG.)	27			
ASPECT ASSUMED	KNOWN	/	KNOWN	
MIN,MAX,INC ASPECT	0 10 10,	40 50 5,	80 90 10	
NO OF FREQUENCIES	8			
NO OF TARGETS	10	15	10	
90% CI (@30%) +/-	3.4%	2.8%	3.4%	
CLASS. FEATURES	T	T	T	
ASP ERR IN CURVE	1	2	3	

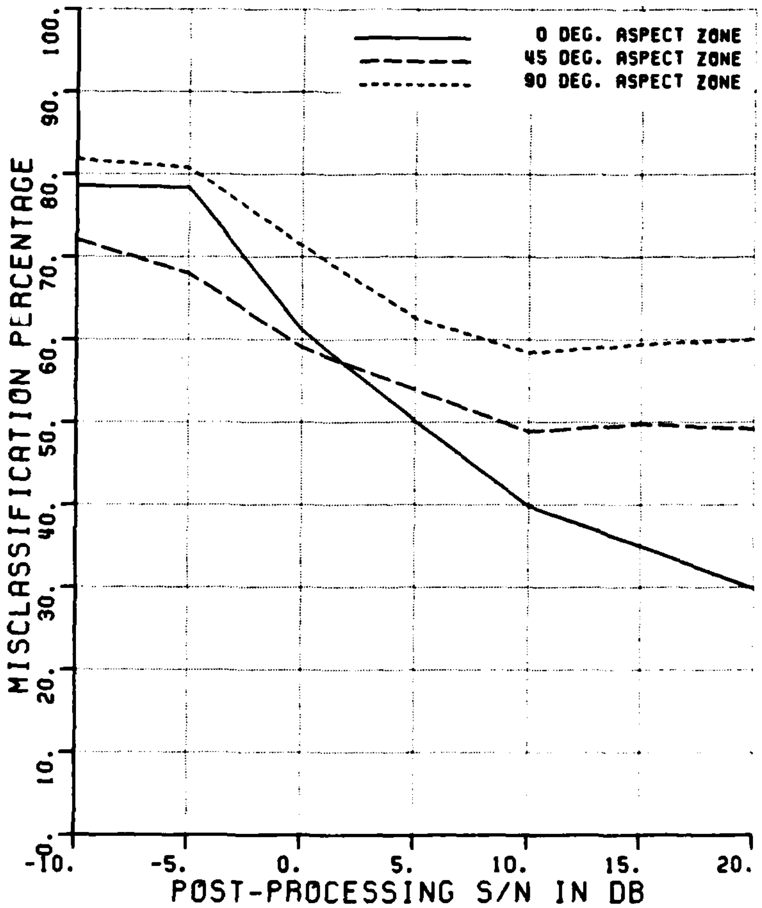


Figure A.80 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones, with a forced error in aspect angle.

CLASSIFICATION OF GND VCLS			
POLARIZATION	V/H		
ELEV ASSUMED	KNOWN		
ELEVATION (DEG.)	27		
ASPECT ASSUMED	KNOWN	/ KNOWN	
MIN,MAX,INC ASPECT	0 10 10,	40 50 5,	80 90 10
NO OF FREQUENCIES	8		
NO OF TARGETS	10	15	10
90% CI (@30%) +/-	3.4%	2.8%	3.4%
CLASS. FEATURES	T	T	T
ASP ERR IN CURVE	**1**	**2**	**3**

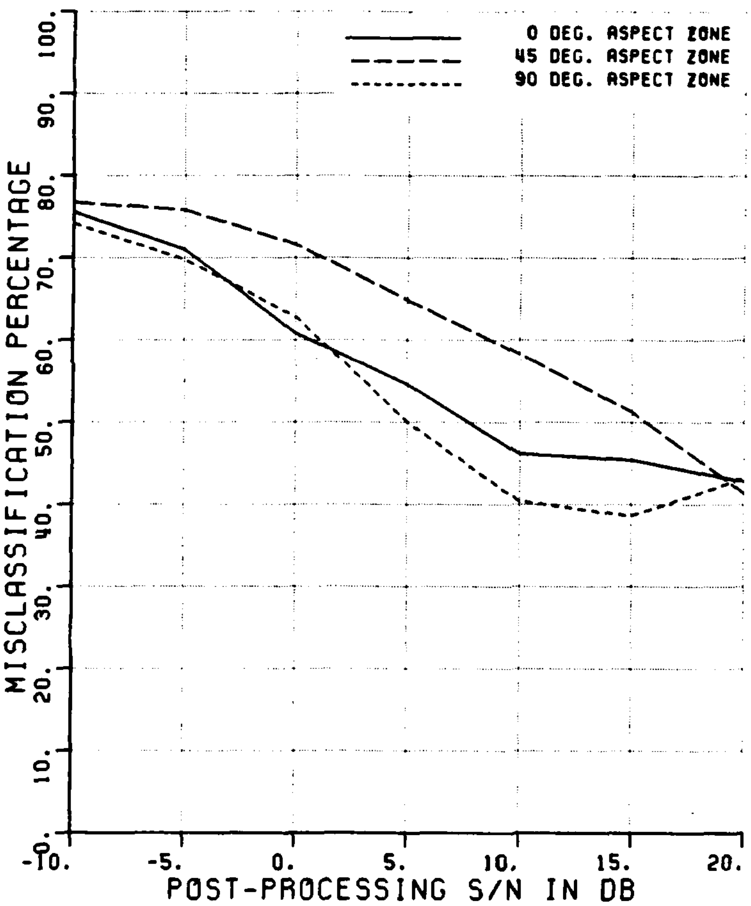
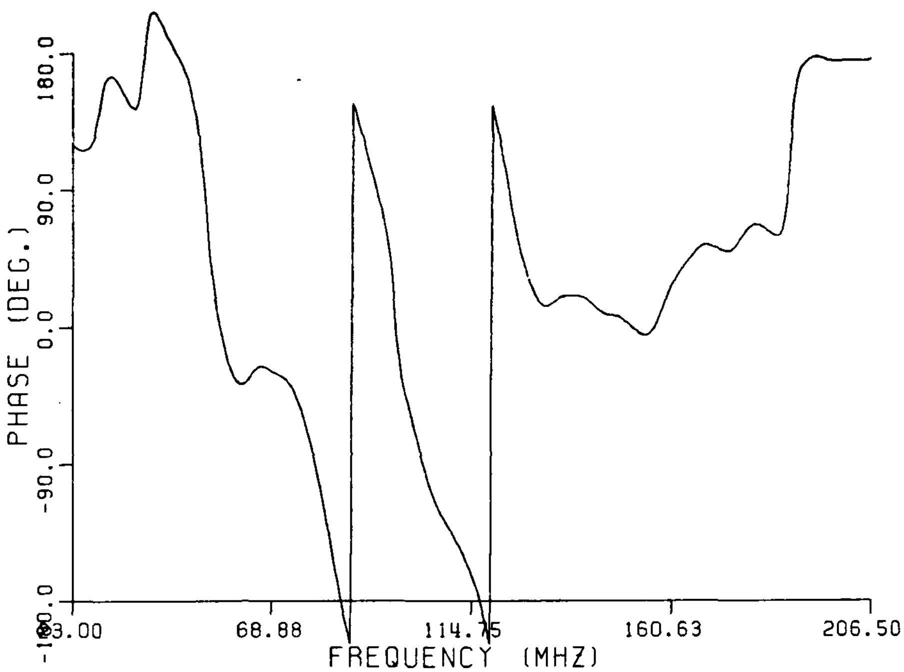


Figure A.81 Misclassification percentage versus post-processing SNR, comparing the performance of various aspect zones, with a forced error in aspect angle.

APPENDIX B

AMPLITUDE AND PHASE RETURNS

This appendix contains plots of the amplitudes and phases of processed radar returns for one vehicle at 3 aspect angles (0°, 45° and 90°), at 27° elevation angle, using vertical and horizontal polarizations.



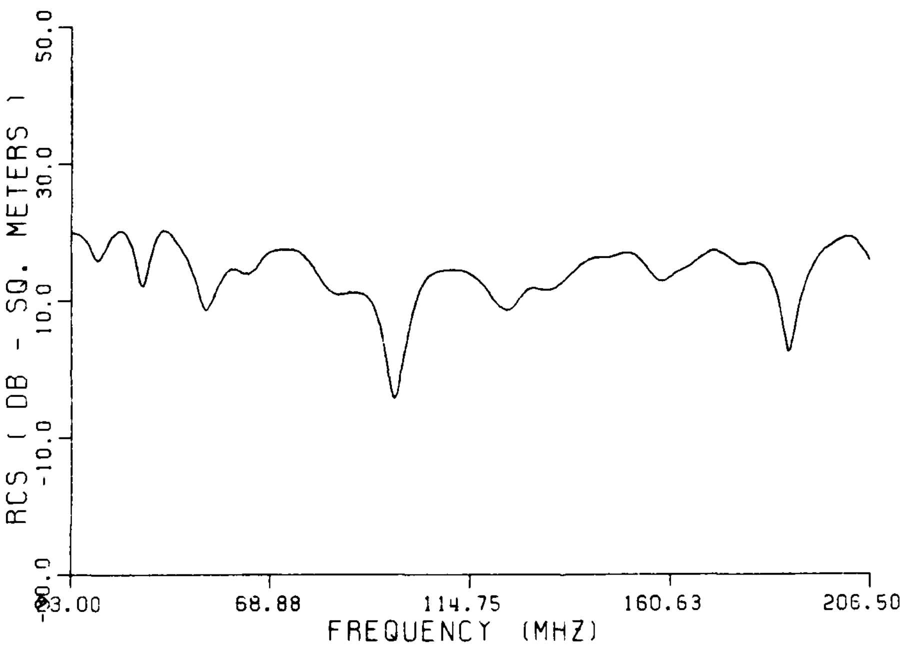


Figure B.1 RCS magnitude and phase response for Vehicle A, at 0° aspect zone using vertical polarization.

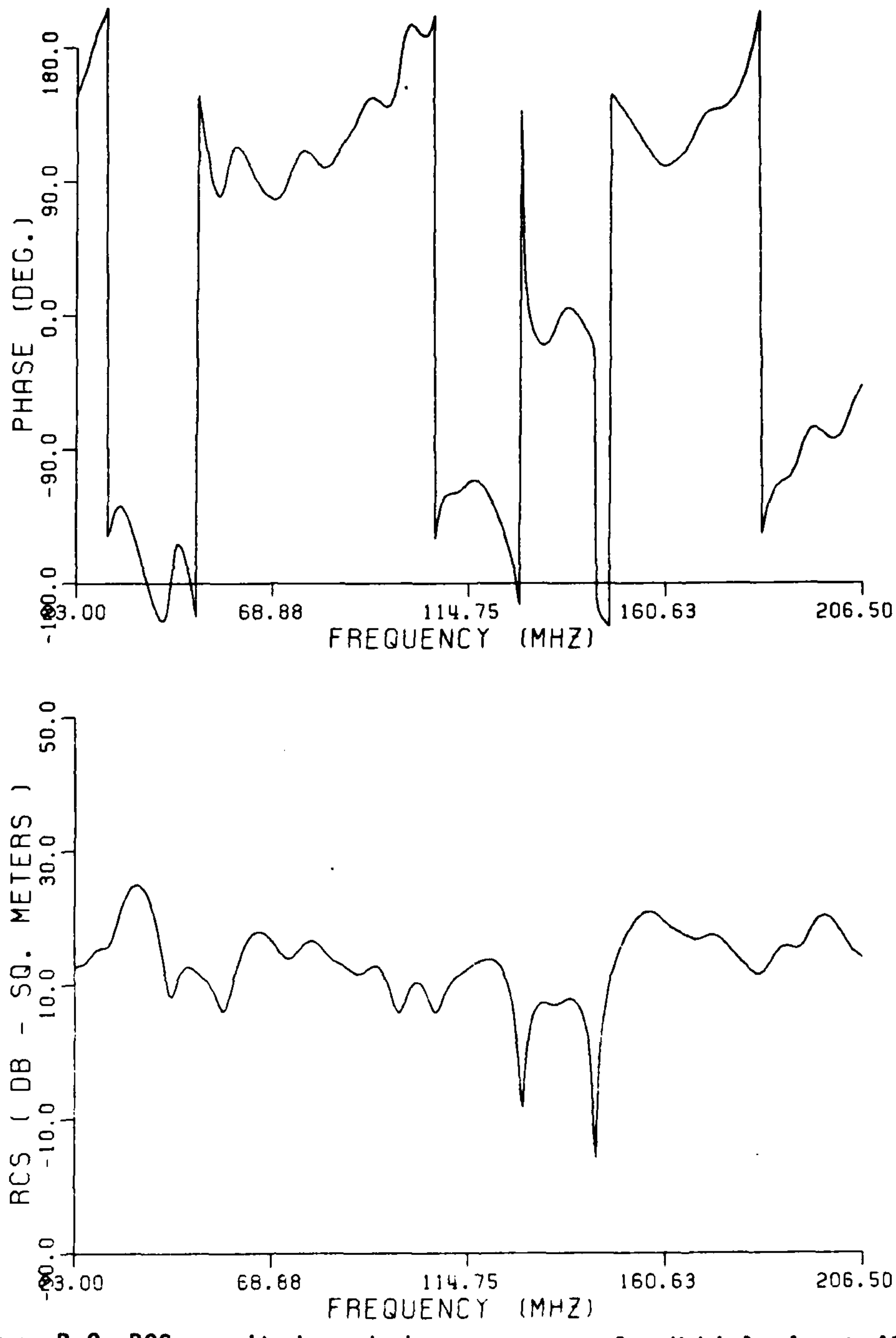


Figure B.2 RCS magnitude and phase response for Vehicle A, at 45° aspect zone using vertical polarization.

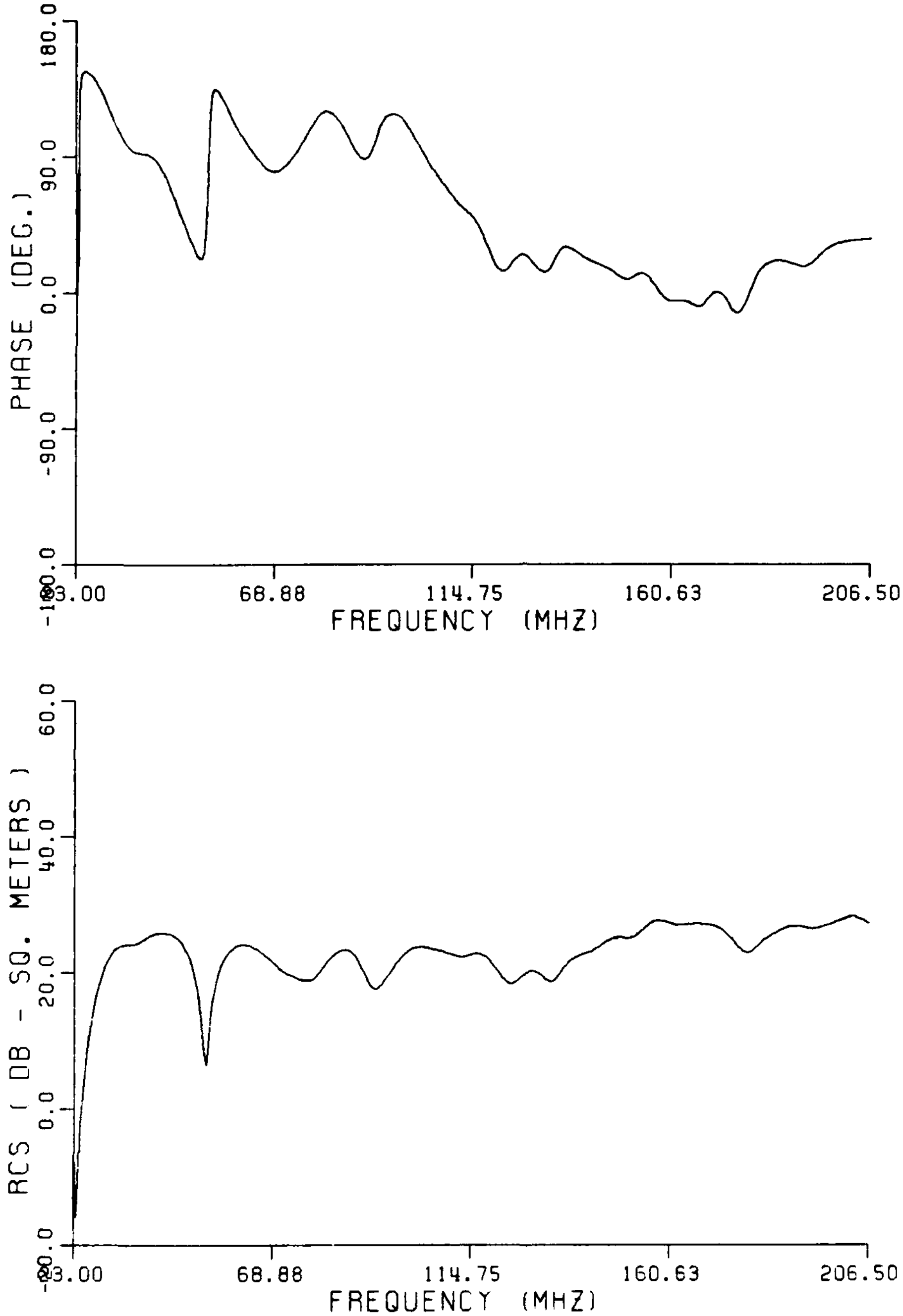
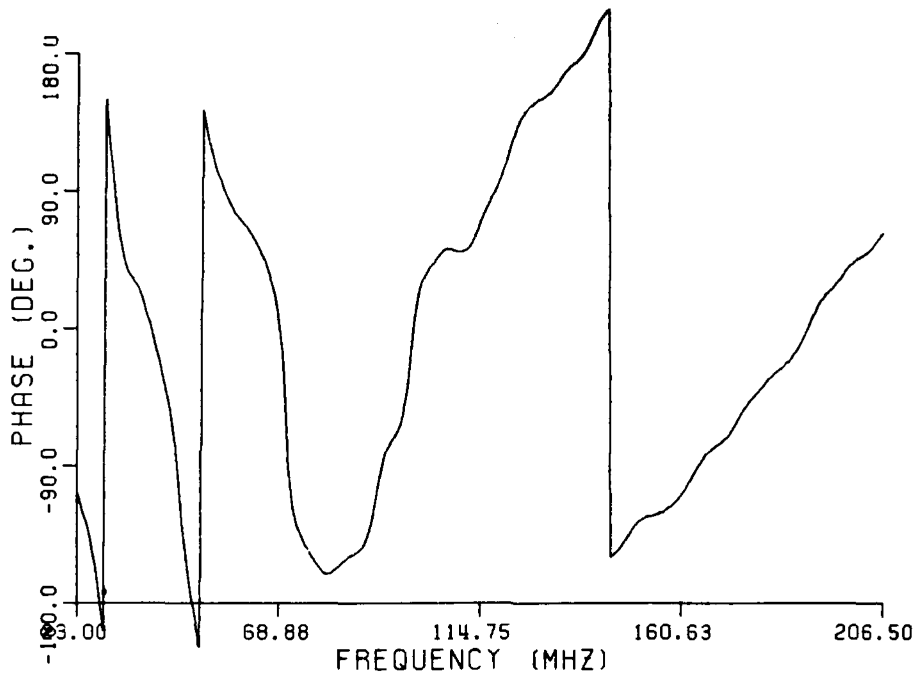


Figure B.3 RCS magnitude and phase response for Vehicle A, at 90° aspect zone using vertical polarization.



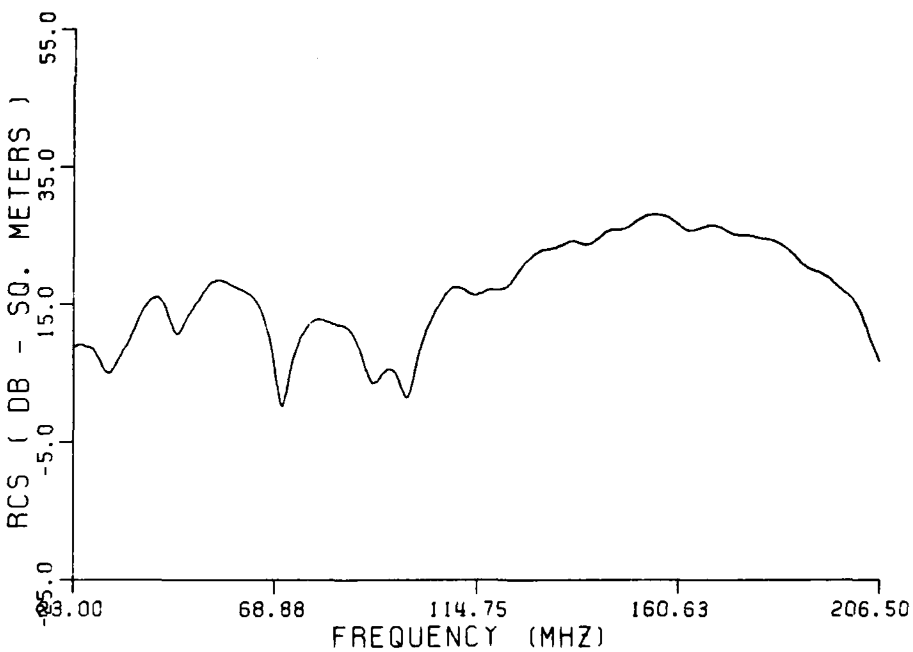


Figure B.4 RCS magnitude and phase response for Vehicle A, at 0° aspect zone using horizontal polarization.

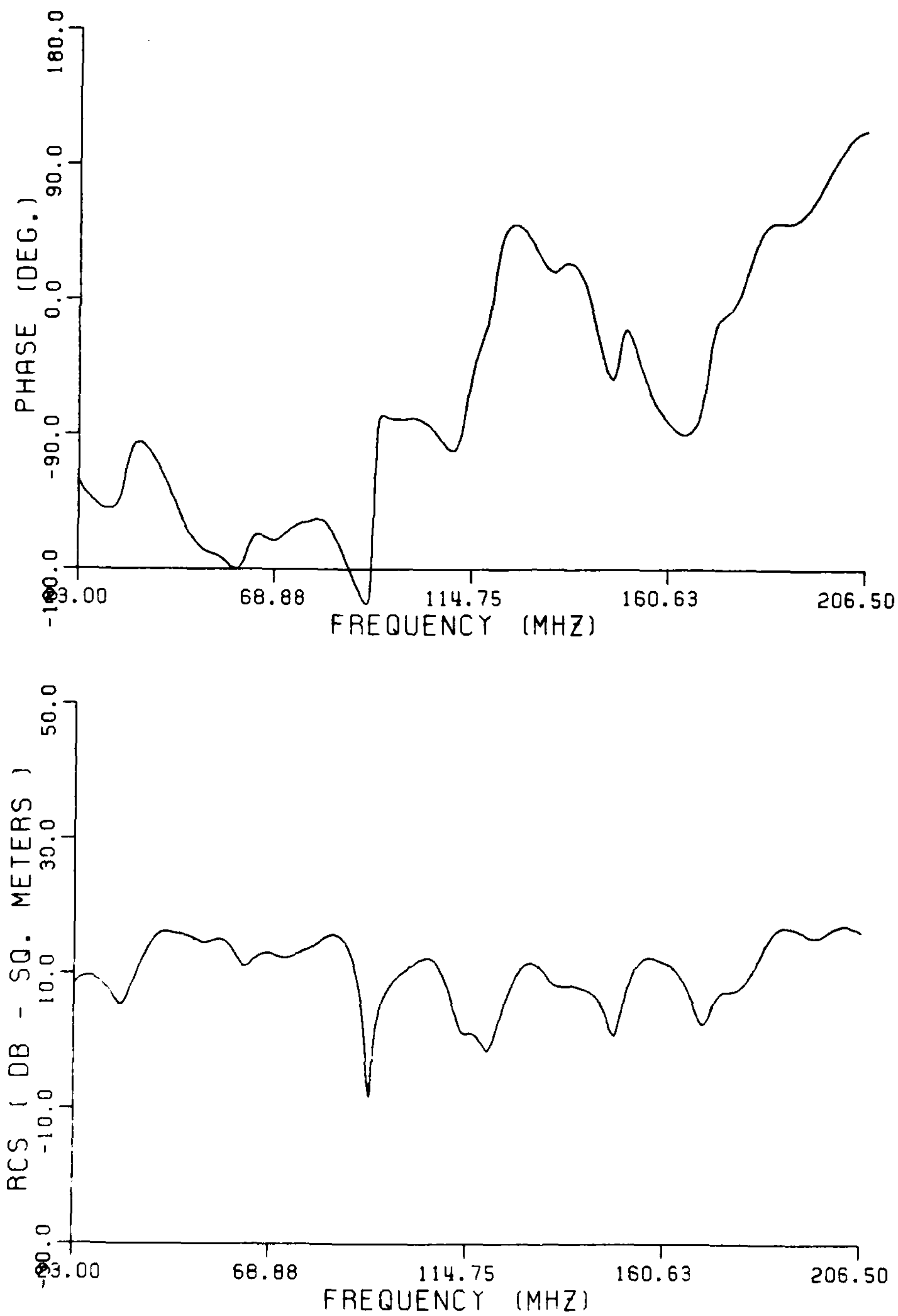


Figure B.5 RCS magnitude and phase response for Vehicle A, at 45° aspect zone using horizontal polarization.

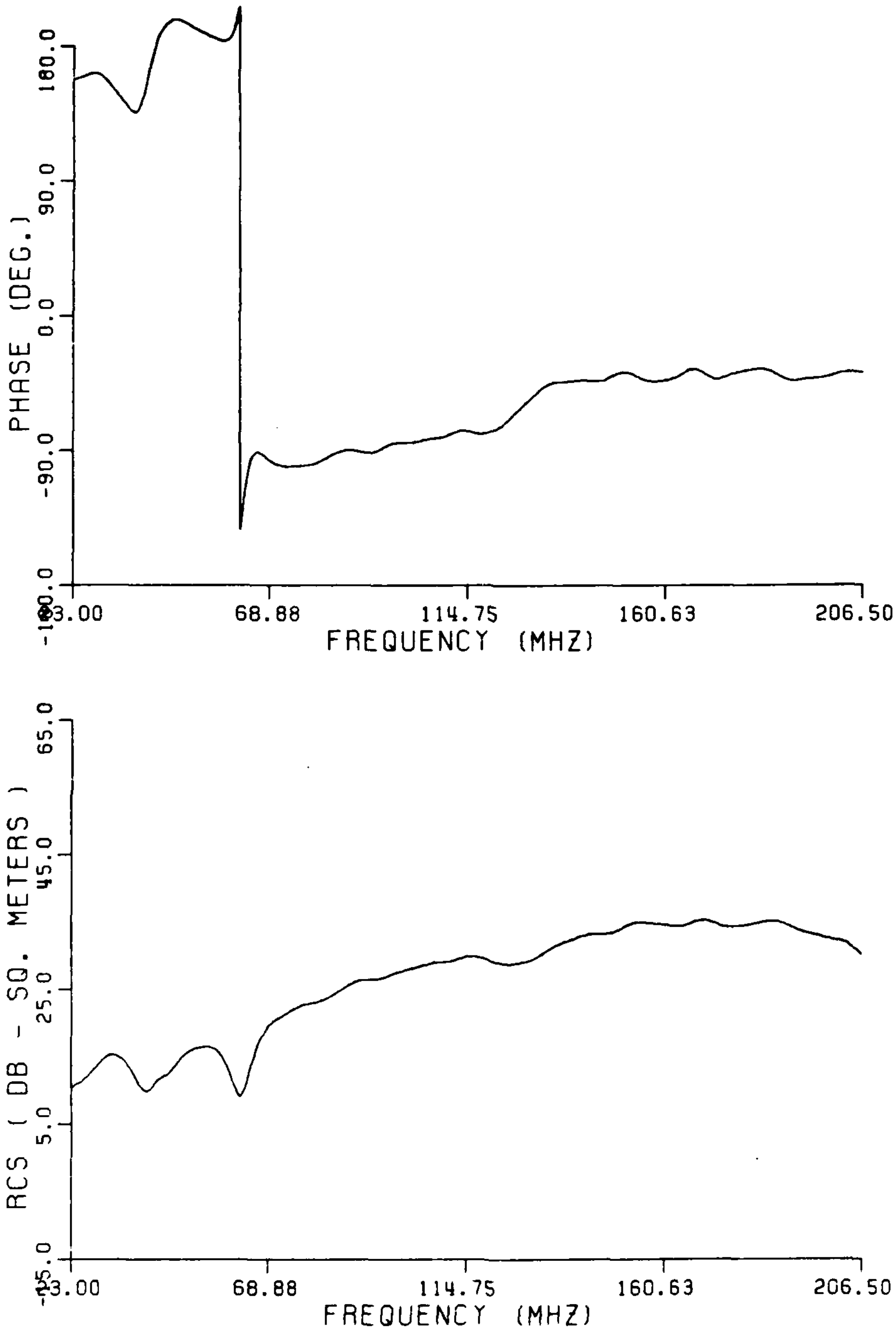


Figure B.6 RCS magnitude and phase response for Vehicle A, at 90° aspect zone using horizontal polarization.

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